2014

Automated logistic processing and downtime analysis of commercial level multi-pass corn stover harvesting systems

Jeff C. Askey
Iowa State University

Automated logistic processing and downtime analysis of commercial level multi-pass corn stover harvesting systems

by

Jeffrey Clark Askey

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Agricultural and Biosystems Engineering

Program of Study Committee:
Matthew Darr, Major Professor
Brian Steward
Carl Bern

Iowa State University

Ames, Iowa

2014

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ABSTRACT

As cellulosic ethanol production reaches commercial scale, it is important to maximize efficiencies throughout the supply chain in order to keep an economically feasible feedstock. One important sub-process is the harvesting of feedstock that will be converted into ethanol. The cost to harvest and transport corn stover is a large component of the total cost and is estimated at $82/std. ton; however, this can be reduced to $47/std. ton with improvements to the supply chain (Shah, 2013).

For a large scale facility, capable of producing 30 million gallons of ethanol, 375,000 tons of dry material per year will be required to keep the facility running at full capacity; this material will need to be harvested from approximately 190,000 acres, based on a two ton per acre take-rate. The main harvest method is a multi-pass system that requires several agriculture machines working in synchronization to produce a dense and transportable material. Over 200 tractors coupled to shredders, balers and stackers are required in order to achieve the full harvest within 30 day window.

The objective of this research was to automate the analysis of Geographical Information Systems (GIS) data in order to provide more adequate real time performance of crews and machines that will drive key supply chain assessments. Results of this work analyzed production scale harvest data during the fall of 2012 and 2013; during 2012 6,000 hectares were harvested while 24,300 hectares were harvested in 2013. The results of this research will benefit cellulosic harvesters, processors and analyzers by providing informative supply chain logistics.

CHAPTER 1. GENERAL INTRODUCTION AND REVIEW OF LITERATURE

In recent years, there has been a public drive to transition from petroleum based fuels and products to more biorenewable products that aren't derived from fossil fuels. There are several key reasons this transition is taking place, the main ones are energy security and environmental impact.

Energy security is a world issue; only so much petroleum exists, and the natural production of petroleum from fossils takes millions of years. Eventually the supply of petroleum will dwindle out or become economically unfeasible to obtain. This concept was derived by Marion King Hubbert in 1956 and is commonly referred to today as "Hubbert's peak" (Hubbert, 1956). Hubbert had defined production to be symmetrical in the shape of a "bell curve" with the center and highest point or peak being the maximum production where about half of petroleum is extracted. The first segment of the curve, which steadily increases, is where the petroleum resources are easily extracted, abundant, and cheap, which leads to economic growth and investments into further extraction (Hubbert, 1956). Production then hits the peak, where the readily-available resource has been depleted and further extraction leads to increasing costs. Many countries have already hit peak oil production and have turned to importing petroleum or alternative fuels.

Energy security is also a national issue. Only a few countries have petroleum under their soil, and many of these places are either in conflicted areas or require going through a conflicted territory. Causing rising prices as well as issues with actually obtaining petroleum without means of war; oil rigs and ships can be damaged or blockaded or even just shut off. With such a heavy reliability on petroleum for transportation fuel, a more secure fuel is needed that can be produced within a nation.

In recent years, focus on greenhouse gas emissions is of a growing concern because when gasoline burns, it releases carbon dioxide that has been sequestered, or stored, underground for millions of years. The release of this carbon dioxide is thought to make weather patterns vary more and also cause an increase in world temperatures, known as global warming. In 2013, the level of carbon dioxide in the atmosphere was measured to be about 400 ppm (parts per million); prior to the industrial revolution, the atmospheric carbon dioxide oscillated between 180 and 280 ppm (Gillis, 2013). A maximum threshold of 2^{o}C rise in total global average temperature relative to pre-industrial levels has been set by European Union. In order to stay below this threshold, it is thought that the levels of atmospheric carbon dioxide need to remain below 450 ppm (Hassol, 2011). In order to stabilize global temperatures under this threshold by year 2050, global emissions would have to be reduced by 60%, while industrialized countries would have to have a reduction of approximately 80% (Hassol, 2011). When gasoline is compared to corn-based ethanol, emissions can be reduced by 52% while cellulosic-based ethanol can reduce emissions by 86% (Wang et. al., 2007).

This paper focuses on the supply of feedstock, particularly corn stover which is a carrier of cellulosic material that can be converted to cellulosic ethanol fuel. Corn stover is abundant in the Midwestern United States and is readily available. In order to understand the crew and machine performance associated with a corn stover supply chain, a 6,000 hectare harvest and a 24,300 hectare corn stover harvest were conducted in 2012 and 2013, respectively, in Iowa to determine key performance metrics and downtime associated with harvest. Windrowing shredders and large square balers are a common way to collect, densify, and package the material. Each implement was coupled to a tractor, and each tractor was instrumented with data logging equipment, allowing performance parameters to be captured and analyzed.

Literature Review

In 2005, the Environmental Protection Agency (EPA) created the renewable fuel standard (RFS) under the Energy Policy Act, which set forth the first renewable fuel mandates for the United States. In 2007, the RFS program was expanded when the Energy Independent and Security Act was created. Diesel was added to the standard, and the volume increased into blended transportation fuels from 9 billion gallons in 2008 to 36 billion gallons by 2022. New categories were created for renewable fuel with separate volume requirements. Cellulosic ethanol was projected to be at 16 billion gallons by 2022. Performance thresholds standards were also set to ensure biorenewable fuel emits lower greenhouse gases than petroleum fuel it replaces.

Cellulosic ethanol is a biorenewable fuel derived from lignocellulose plant materials. Corn stover, the entire corn plant above the surface excluding the grain, is one of the main cellulose carriers and is a common residue product of corn (Wyman, 2008). Corn stover has an approximate mass yield of 1 to 1 when being compared to corn grain yield (Ertl, 2013); this means for every pound of grain, a pound of corn stover exists. In 2012, Iowa produced 1.88 billion bushels of corn grain, while the United States produced a total of 10.78 billion bushels (USDA, 2013). Figuring 56 lbs/bushel, this equates to about 52 million tons of corn stover produced over an area of 13.7 million acres for Iowa. Theoretically, one dry ton of corn stover yields 113 gallons of cellulosic ethanol (AFDC, 2012); however, a more practical number is 80 gallons per ton. If all of Iowa's corn stover were to be collected, 4 billion gallons of cellulosic ethanol could be produced; however, due to environmental and economic considerations, only partial harvest of corn stover can and should be accomplished. It was estimated that the United States in 2009, had a sustainable 76 million dry tons of stover available for fuel conversion and by 2020, 112 million dry tons of corn stover will be available (NAS, 2009).

With this abundant supply of corn stover, Iowa has been targeted along with the Midwestern United States to produce cellulosic ethanol from corn stover. Three cellulosic bio-refineries are currently being constructed in the Midwestern United States, to supply the demanded cellulosic biofuel and will be operational within the next year. Two of the plants, POET and DuPont are located in Iowa, while Abengoa is located in Kansas. POET's Project Liberty began construction in late 2011 and is expected to produce 25 million gallons of ethanol. At full capacity, 285,000 dry tons of feedstock is needed and will come from approximately 285,000 to 300,000 acres within a 35 mile radius (POET, 2012). DuPont is scheduled to open a commercial-scale cellulosic ethanol facility in the latter part of 2014. Once in full production, it is estimated this facility will require 375,000 dry tons of cellulosic material and produce 30 million gallons of ethanol (DuPont, 2012). Within a 30 mile radius of the facility, 815,000 acres of corn stover exists; however, the facility will only require 190,000 acres to be harvested within a limited time frame. Abengoa started construction in the summer of 2011, for a 25 million gallon facility. The facility is expected to need 320,000 dry tons of feedstock per year, coming from an estimated 150,000 to 200,000 acres within a 50 mile radius (Abengoa Bioenergy, 2011).

All three plants face challenges throughout the entire process and must conquer these new challenges in order to successfully implement cellulosic ethanol production. Once in full production these facilities will need a combined 980,000 tons of cellulosic feedstock.

The supply chain of corn stover is considered to be from the time the material is ready to be harvested in the field to the time it reaches its final destination to be converted into ethanol. One key process of the supply chain is gathering, densifying and packaging the material into bales before it can be shipped. Production of corn stover bales requires three key pieces of equipment, a windrowing shredder, a large square or round baler, and stacker wagon (Darr, 2012 Nov.). The windrowing shredder chops the material and produces a windrow, a row of material for the baler to pick up (Figure 1). Large square balers utilize mechanical forces to compress the material into a dense rectangular bale, typically 4 ft. wide, 3 ft. high and 8 ft. long, while a round baler uses rotating tensioned belts to create a bale. Bale shape depends on the end consumer's preferences and supply chain demands. A stacker wagon is an efficient way to collect large bales in-field and move them to a field entrance. From here, bales are transported to a larger storage location near the facility, or to the facility for processing. It is crucial that the equipment is properly managed in order for all the material to be successfully harvested during the limited harvest window.

Figure 1: Corn stover being baled into large square bales

During the process of producing bales, it is important that the baled material is relatively low in moisture, and also low in ash content. High moisture bales degrade quickly due to microbial activity, and are hard to handle after prolonged storage, which is why low moisture material is preferred. Ash content includes anything that is not able to be converted into ethanol which consists of two components: very little structural ash from plant material, and soil that is brought into the bale from windrowing or baling processes. Ash is a contaminant and economic disincentive to the baling process and therefore should be kept to a minimum.

With current harvesting equipment technologies, over 200 tractors coupled to shredders, balers and stackers are needed in order to harvest the material within a 30 day harvest window, per facility. Harvesting corn stover is a large component of the total cellulosic ethanol cost. It is estimated that the cost of harvesting the corn stover and transporting to the plant costs about $82/ std. ton; however, with supply chain improvements this can be reduced to $47/std. ton (Shah, 2013). Windrowing, baling and stacking make up 45% of the total supply chain cost. One way of reducing the costs during harvest is to increase harvesting efficiencies through better management techniques. A harvest of this size requires accurate and informative data in order to make key decisions that will drive supply chain assessments.

Geographical information systems (GIS) data contains various types of information linked directly to specific GPS (Global Positioning System) coordinates. This allows data to analyzed spatially in detail, it also allows for multiple attributes to be pulled together and analyzed at one given point in the field.

GIS systems allows for decision support systems (DSS) to be developed, this offers a tool which takes complex systems and creates structured analysis tools for data analytics (Reddy & Rao, 1995). Spatial decision support systems are crucial for systems such as crop productivity management, watershed management, and precision farming (Reddy & Rao, 1995). Precision farming utilizes GIS systems to develop prescription maps, build yield maps, and support decisions. DSS reduces operator on-the-spot management and allows decisions to be made ahead of time in order to capture the fullest productivity out of the field, while reducing input costs. Crop productivity management brings together all variables that impact crop growth, such as soil types, elevation, yield, slope and many other attributes. This allows managers to make decisions based on complex information on a spatial layout. Decisions are typically based on qualitative and quantitative methods; typically quantitative analysis provides recommendations for managers (Heinemann, 2009). Heinemann (2009) stated “management of agricultural production operations can be complex and daunting.”

Machine information data can be obtained from tractors and implements through the controller area network bus (CAN Bus) (Darr, 2012 Sept.). The data that is transmitted over the CAN bus by the tractor provides important machine parameters such as engine speed and power take off (PTO) speed. Implements, such as large square balers, transmit data across a network bus that utilizes the J1939 standard protocol (SAE, 2013), which is typically referred to as the ISOBUS; this provides parameters such as bale count and flake count on a baler. The CyCAN logger is a logging instrument has been commonly used by Iowa State University researchers (Figure 2; Covington 2013, Peyton 2012 and Webster 2011).

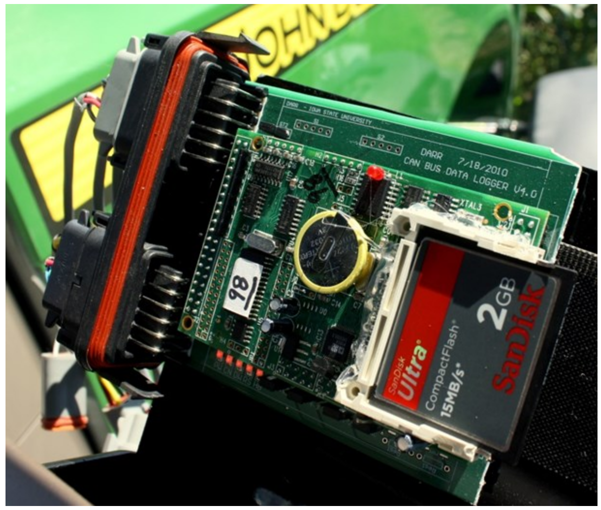

Figure 2: Installed CyCAN Logger connected to the ISOBUS diagnostic port

The CyCAN logger filters for unique CAN messages and merges this information with GPS coordinates to enable the data to be spatially analyzed as GIS data. Webster (2011) used GIS software to analyze productivity and cost associated with a single-pass harvesting system, by capturing CAN data such as engine speed and fuel rate. Peyton (2012) utilized GIS software to analyze data using spatial querying and filtering, enabling for a detailed performance evaluation of multi-pass corn harvesting systems. In-field parameters were used to calculate management terms such as theoretical area and material field capacity. Multiple machine types were evaluated including windrowing shredders, rakes, stackers and balers.

Covington (2013) captured CAN data and utilized GIS to define a set of machine utilization parameters in order to determine with certain confidence what the tractor and implement were doing throughout the day. The analyzed data is used to determine how much time was spent in production, idling or in transportation. This information allowed for the detailed analysis of multi-pass harvesting systems.

Previous research was accomplished using small data sets and GIS software to analyze the data after harvest. The limitation of the previous approaches is the amount of time needed to process large amounts of data in a commercial scale harvesting system, while providing accurate information.

Objectives

The objectives for this research were as follows:

- Develop an automated approach to filtering and analyzing biomass supply chain Geographical Information Systems (GIS) data
- Standardize a set of performance metrics for rapid determination of machinery and crew harvest performance
- Develop automated downtime analysis of biomass supply chain data
- Determine root cause of in-field idle instances further assessed into major machinery malfunctions and organizational logistic issues

Thesis Organization

This thesis contains a general introduction of the topic, two research chapters, and an overall conclusion. The general introduction includes a statement of the primary purpose and objectives of the thesis along with a description of the thesis organization, a statement from the authors defining his primary rolls in the research along with a synopsis of the literature review.

The first technical chapter, entitled "Automated Logistics Processing of GIS Data for Agricultural Harvest Equipment," describes how the performance metrics were extracted and the impact the metrics have on supply chain assessments. The second technical chapter, "Automated Downtime Analysis of GIS Data for Agricultural Harvest Equipment," describes the downtime associated with harvest equipment during full production scale harvest during 2012 and 2013.

Authors' Role

The primary author, with the assistance and guidance of co-author Dr. Matthew Darr, composed the research chapters presented in this thesis. Unless otherwise indicated, all procedures were performed by the primary author.

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CHAPTER 2. AUTOMATED LOGISTICS PROCESSING OF GIS DATA FOR AGRICULTURAL HARVEST EQUIPMENT

Abstract

Technological advancements have significantly eased the communication and control of today's agricultural equipment. Today, the majority of machine functions communicate and are controlled through the vehicle's controller-area network (CAN) bus. By accessing the CAN bus on a machine, it is possible to capture and mine an enormous amount of data that can unlock knowledge about its performance. Collecting and properly analyzing this data allows gathering information that is useful for better management of machines, which leads to enhanced machine efficiencies and increased productivity. The main objective of this study was to automate the processing of the Geographic Information System (GIS) data collected through CAN bus systems.

GIS data allows for specific machinery parameters to be linked to a specific GPS (Global Positioning System) location. The GIS data can then be sorted and mapped spatially on a per-field basis, allowing for each field to be processed and analyzed separately. Processing this data using specifically defined metrics allows the data points to be sorted into discrete machine categories, such as "Active" and "Idle". Considering the amount of time required to perform such operations manually, this study will automate the logistics processing of GIS data, to reduce turnaround time from raw data to final results. Machine data was obtained during a large production harvest of stover during the fall of 2012. A logical approach of filtering and comparing data, through programming, allowed large data sets to be quickly analyzed. These instances were then compared in order to drive system improvements, such as efficiencies and productivities of farm machineries. In 2013 an increase of 7.5 percentage points was seen in baler productivity compared to 2012, while idle decreased by 8.5 percentage points. These instant performance metrics will drive overall supply chain evaluation of key indicators including productivity and efficiency.

Introduction

Cellulosic ethanol production has begun to transition towards commercial scale; this is, in part, due to the Renewable Fuel Standard (RFS), which mandated the minimum volume of biofuel to be used for fuel. While the cellulosic biofuel requirement was projected to produce 6 million gallons in 2010 and 2011, zero gallons were actually produced. This is expected to grow to 16 billion gallons per year of cellulosic ethanol by 2022 (EPA, 2009).

In order to provide an economically feasible product, it is important to maximize efficiencies throughout the process. One important sub-process is the act of harvesting the feedstock that will be converted to ethanol. For a commercial scale cellulosic facility, capable of producing 30 million gallons of ethanol, in full production, it will take about 375,000 tons of dry corn stover per year; this material will need to be harvested from approximately 190,000 acres based on a two ton per acre take-rate (DuPont, 2012). The main harvest method of corn stover is a multi-pass system that requires several agriculture machines working in synchronization to produce a dense and transportable material of desired quality. It is crucial that the equipment is properly managed in order for all the material to be successfully harvested during the limited harvest window. Obtaining corn stover is a large component of the cost, it is estimated that the cost of harvesting the corn stover and transporting to the plant costs about $82/std. ton (Shah, 2013).

Keeping dozens of machines in synchronization and working together takes a great deal of monitoring and management. In order to successfully monitor and control a system, an analysis system needs to be implemented in order to provide informative feedback. Feedback aides in managerial decisions that drive overall supply chain assessments and allows for adjustments in the process to maximize efficiencies and to move closer to the desired output. Having feedback after the project or process is complete provides virtually no help to the completed process, but allows for following processes to be changed based on what was learned from the previous process. With the harvest process only spanning across a few weeks and occurring once a year, it is important to monitor the process throughout the harvest season in order to make adjustments to meet the targeted goals set by quality and time to ensure the full project will be completed within deadlines. Processes which support real time analysis will offer significant benefits to the supply chain operation.

The previous method of analyzing data was done manually using GIS software, working with small amounts of data; however, as harvested acres increases, so does the amount of data and complexity. A large amount of data is cumbersome to filter manually, and takes away resources that could be better utilized elsewhere. The data has previously been collected at the end of the season and has been used to understand successes and challenges within the supply chain, and changes were then implemented the next year to improve efficiencies of the equipment. This, however, does not allow for daily feedback and improvements, for a large scale commercial harvest, it is crucial to monitor and control the system throughout the harvest.

An automated system can be implemented to logically filter the data into specific parameters and reduce the amount of time it takes to process the data. The time to analyze the data can be reduced to several minutes compared to several days or weeks. This allows for an improvement to be made in the way data is recorded and how it is received. It allows for more immediate feedback of the process, and a better way to manage and control the current harvesting process.

Research Objective

The objective of this project was to develop an automated approach to filtering and analyzing GIS data, allowing for rapid determination of machinery and crew performance. These instant performance metrics will drive improvements in key indicators for biomass supply chain success including productivity and efficiency.

Materials

Data Logging Instrument

Machine data was captured using CyCAN loggers, developed by Matt Darr at Iowa State University in Ames, Iowa. The logger software filtered for specific parameter group numbers (PGN) on the implement bus. The J1939 standard (SAE, 2013) was used to determine which PGN numbers were desired, based on the signals contained within that specific message. CyCAN also contained serial ports that utilized the RS-232 protocol to capture GPS information, such as date, time and global coordinates. Data was recorded at one-second intervals when the tractor was keyed on, and the data was saved to a memory disk. The data was collected at the end of the harvest season to be analyzed. Multiple machine parameters were recorded, such as tractor engine speed, vehicle ground speed, global coordinates, PTO speed, bale counter, fuel rate, date and time.

Data Processing

Microsoft Visual Studio was used to develop a visual basic script to automatically process the data, based on certain machinery information and parameters. The processed data was then analyzed into specific key metrics based on what is useful information for the supply chain assessment.

Equipment Used

In 2012, Hiniker 20 foot side discharge shredders (model 5620) were utilized to chop the stalks and to simultaneously create windrows of material for the balers to pick up. In 2013, the shredders used were Hinker model 5620HH, which work the same as the 2012 model however had an additional feature. In 2013 a hydraulic swinging tongue was added to easily transition between transportation mode and field mode. Shredders, in both 2012 and 2013, were driven with tractors that had at least 225 horsepower output at the PTO.

Three crews in 2012 utilized AGCO’s large square baler (model LB34B XD), which produced bales 3 ft. by 4 ft. wide and 8 ft. long. Crew four utilized Krone large square balers which produced a bale the same size as the AGCO baler. In 2013 all crews used AGCO large square balers. Balers, in both 2012 and 2013, were driven with tractors that had at least 300 horsepower output at the PTO.

Harvest Logistics for Raw Data Set

During the corn stover harvest, fall of 2012 in Iowa, a data logging instrument, CyCAN, was installed on ten shredders and nine balers across four different crews that harvested a total of 6,000 hectares and produced approximately 37,000 bales. Over 2,800 hours of CAN and serial data were captured and recorded from these nineteen machines, within a harvest window of 50 days. Each of the four crews had a work area around central Iowa and was assigned fields as the grain harvest was completed. The crews were tasked with windrowing the stover, baling, and producing a field edge stack, which would be later moved by other means.

During the harvest of fall 2013 in Iowa, a second generation telemetry system was installed on over 100 machines that harvested approximately 24,300 hectares and produced over 172,800 bales. The second generation telemetry system contained all the features and capabilities of CyCAN, plus several additional features. The logging device utilized telematics to transmit data every 15 seconds to a server, where the data was stored, analyzed, and reports were automatically generated and then emailed out to certain individuals. The logging device also had the capability of performing onboard calculations such as real time productivity. Ten crews were utilized to collect, densify and stack the corn stover at field edge.

Methods

Machine Utilization Parameters

Parameter metrics were defined to rank the machinery parameters into three discrete categories; production, idle and transportation. In order to be classified into the production category, several criteria had to be met. The engine speed needed to be greater than 1700 rev min^{-1}, PTO speed greater than 650 rev min^{-1} and the vehicle speed was between 2 and 17 km h^{-1} (Covington, 2013). Idle requirements were defined when vehicle speeds dropped below 2 km h^{-1}, with the PTO, and the engine running at any speed (Covington, 2013). Transportation was defined when the PTO was below 650 rev min^{-1} and the ground speed was greater than 2 km h^{-1} with the engine running at any speed (Covington, 2013).

While Covington (2013) investigated data within fields using GIS software, the focus in this research was on a daily basis and included data within field as well as outside of fields, such as transportation from field to field. For this reason, secondary transportation requirements were further broken down in order to account for road transportation as well as in-field transportation. Field transportation requirements used were vehicle speeds between 2 km h^{-1} and 30 km h^{-1}, while PTO was below 650 rev min^{-1}. The second transportation category, road transportation, was when vehicle speed was equal to or above 30 km h^{-1} and the PTO is turned off (0 rev min^{-1}). A set cut off limit of 30 km h^{-1} was chosen as a speed cutoff due to the fact that 99.95% (# of points = 5,692,450) of field speeds fell below this cutoff, and 73.01 % (# of points = 1,285,923) of out of field transportation fell above this cutoff (Figure 3). The data is classified into two distinct categories, “Field” and “Road”. The data was geo-fenced utilizing field boundaries, the data within the boundaries was classified as “Field”, while the data outside of the boundaries were classified as “Road”.

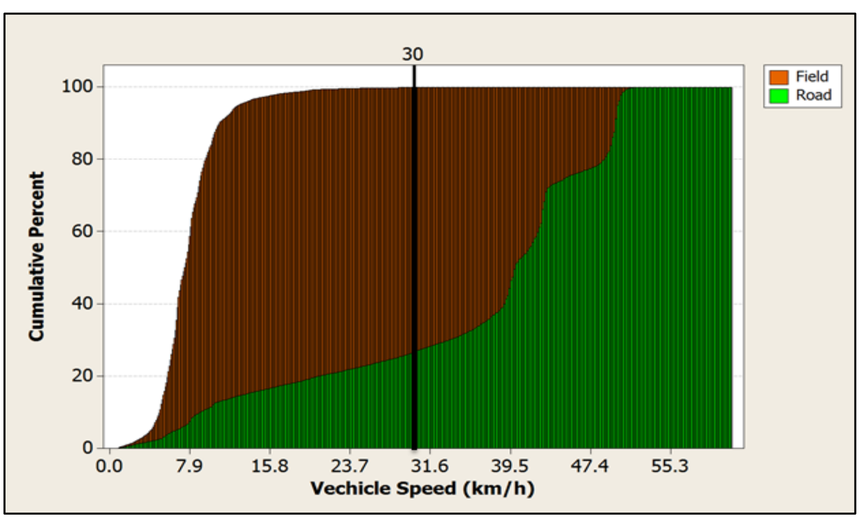

Figure 3: Machine field transportation speed compared to road transportation speed

In order to reach road speeds, the vehicle must first pass through lower speeds, the vehicle must also slow down to lower speeds when turning (Figure 4) and coming to a stop. The red dots indicate where the vehicle speed drops below 30 km h^{-1} and the green dots are vehicle speeds above 30 km h^{-1}.

Figure 4: SMS Road Transportation of Tractor-Baler turning

A transportation algorithm utilizing a “look-ahead-behind” duration was implemented in order to better distinguish and capture road transportation. The “look-ahead-behind” duration set how long the machine could go out of being classified as road transportation before going back into road transportation to still be considered in road transportation, in order to account for turning and stopping. For instance, in the previous Figure 4, the machine drops out of road transportation for a duration of approximately seven seconds, in order to turn at safe speeds, if the seven seconds is less than the “look-ahead-behind” duration than that time it is considered to be road transportation instead of field transportation. The same concept was applied when the machine makes stops at intersections.

With this approach the 26.99% of the road transportation not captured can be reduced to 1.36%, allowing for more accurate analysis. The 1.36% that isn’t captured is idle time, where the machine was at a speed of zero for long durations of time, this occurs when the machine was at a farmstead, and not actually moving from field to field.

The GIS data was geo-fenced based on field locations and separated into two categories: field data and non-field data. The non-field data mostly included transportation between fields; however, it also included data from operations outside of the field, such as idling at a farmstead or shop. The non-field data was analyzed to determine a reasonable “look-ahead-behind” duration in order to capture a majority of the road transportation. Out of all of the machines, the total number of times the tractor slowed below 30 km h^{-1} was 4774 occurrences, and the time durations vary at each occurrence the machine slowed below 30 km h^{-1}. By utilizing a “look-ahead-behind” time of 180 seconds 94.95% of the 4774 occurrences can be captured. Table 1, below, shows the results of an analysis using Tukey’s method to compare values, the “look-ahead-behind” time of 180 seconds was used, as this is the first place the statistical difference begins to steady out. While there is a statistical difference between 120 and 180, there is not sufficient evidence to suggest that there is a statistical difference between 180 and 240 seconds.

Table 1: “Look-ahead-behind” duration and percent of data captured, Tukey's Method; Values that do not share a letter are significantly different

"Look Ahead Behind” Time (Seconds)	**% of Data Captured**	**Tukey’s Method**
15	40.32%	A
30	69.86%	B
60	85.84%	C
120	92.71%	D
180	94.95%	E
240	96.23%	E
480	98.66%	F
960	99.85%	F
∞	100.00%	F

Machine utilization parameters, defined here, allow for an accurate approach of capturing with certain confidence what the machine was doing throughout a day. Bringing together all parameters allows for a rapid technique of analyzing GIS data for crew and machinery performance.

Automated Logistics Processing

Figure 5 shows the basic organization analysis of events that typically occur during harvest; this breakdown set the basis for the methodology. A “Crew Active Duration” exists and was defined as the time between when the key was first turned on until the last event that the key was on. During crew active duration the machine engine was either on or off. The “Machine Active” was said to be if the engine speed was greater than 500 rev min^{-1} since most machines will operate at a lowest engine speed or idle at above 500 rev min^{-1}, except when cranking the engine to start. The "Engine Off" duration was defined as the difference in "Crew Active Duration" and the "Machine Active Duration," or when the engine was below 500 rev min^{-1}. While under the "Machine Active Duration," multiple events can happen, and these events are categorized into three discrete events: production, idle, and transportation. Machine utilization parameters that were discussed in the previous section enable the production, idle, and transportation durations to be captured.

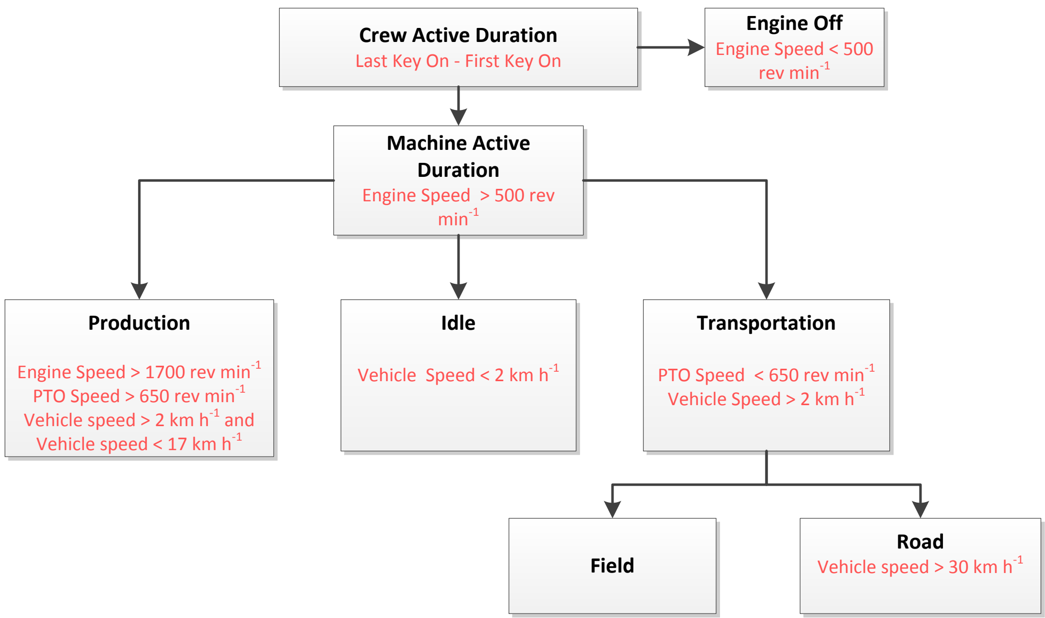

Figure 5: Automated Logistic Processing Organization

While in each discrete event, multiple machine information metrics can be extracted. This allows the operator and managers to have a full harvest summary on a daily basis for each machine.

Metric Summary

A summary of key metrics was the result of the automated logistic processing; the summary was a daily summary that captured information that aided in crew and machine management, such as productivity metrics, idle metrics and transportation metrics. All metric times were reported in standard 24-hour format. This summary was a useful tool, providing feedback that was crucial in assessing the organizational and mechanical capabilities of the crew and machine respectively. The output metrics have been broken down into five categories; General Metrics, General Productivity

Metrics, Baler Productivity Metrics, Idle Metrics and Transportation Metrics. All output metrics are used in combination with each other in order to understand machine and crew performance. However, baler productivity metrics are not utilized when understanding shredder performance.

General Metrics

General metrics were useful to understand the higher managerial decisions of the crews. Table 2 lists out key metrics that were included in the general metric category. These metrics define which crew was running the machine, the date of interest, and important machine start-up information. Machine start and stop coordinates allows managers to see where the machine was physically located at the machine start and machine stop events; this also allows mechanics or technicians to know where to go if the machine needs maintained or serviced.

Table 2: General Metric Summary

Metric	Unit of Measurement
Crew	-
Date	Date
Machine Key On	Time
Machine Last Key On	Time
Crew Active Duration	h
Machine Start	Time
Machine Start Coordinates	Degrees
Machine Stop	Time
Machine Stop Coordinates	Degrees
Machine Active Duration	h
Average Fuel Rate while Machine On	$L\ h^{-1}$

"Machine Key On" was when the tractor ignition key was first turned on by an operator for the day, which doesn't have to be the same time that the operator started the machine. The operator may just want to know how much fuel is currently in the tractor, for example, and doesn't need the machine started. "Machine Last Key On" indicates the last time the tractor key was on at the end of the day. Combining this with "Machine Key On" provides detail on how long the crew was around the machinery for that day and could have been productive; this is referred to as "Crew Active Duration" (Equation 1). The daily window of possible harvest time is crucial when limited on amount of harvestable days.

$$Crew\ Active\ Duration\ (h) = Machine\ Last\ Key\ On - Machine\ Key\ On \quad \textbf{(1)}$$

“Machine Start” and “Machine Stop” show when the engine was first running at the beginning of the day to when it was last running at the end of the day. If the engine speed was above 500 rev min^{-1} this event was classified as the “Machine Active Duration”. The “Machine Active Duration” was useful when looking at how long the engine was running during the total duration of the day. In order for maximum overall efficiencies and productivity, the “Machine Active Duration” should approach the “Crew Active Duration”. These metrics also provide value in knowing how early in the day crews actually get around the equipment, on good production days it is important that crews get to fields early. Average fuel rate is also calculated during “Machine Active Duration”.

General Productivity Metrics

General productivity metrics were useful in quantifying what the crew accomplished with a machine in a given day. Table 3 shows a list of the metrics included with general productivity metrics. These metrics provide assessment on how the crew and machine perform while performing the task at hand.

Table 3: General Productivity Metric Summary

Metric	Unit of Measurement
Production Start	Time
Production Stop	Time
Production Duration	h
Production Average Fuel Rate	L h^{-1}
Production Average Engine Load	%
Production Peak Engine Load	%
Production Average Speed	km h^{-1}
Effective Area Capacity	ha h^{-1}

“Production Start” is the point at which the machine has begun production, as defined by the machine utilization parameters. “Production Start” is compared to the “Machine Start” in order to see whether the machine starts to be productive right away or if there is a time delay. Time delays can be a result of servicing equipment, waiting for the material to be harvestable, i.e. dew evaporated off, baler waiting for the windrowing tractor to get windrows prepared, or equipment to be switched from transport mode to field mode or vice versa.

"Production Duration" is the time amount that the crew used the machine on that day producing a product whether it is a windrow or bale. Not only was it important that the "Machine Active Duration" approaches the "Crew Active Duration" but the "Production Duration" must also approach the "Machine Active Duration," in order to maximize productivity and efficiencies.

These metrics also are used to understand the cost associated with production, such as how much fuel the machinery was utilizing per hour while in production. "Production Average Engine Load" and "Peak Engine Load" is useful in order to understand if the tractor is adequately sized to the implement. If the tractor is undersized, it could result with a reduction in productivity, while if it's oversized it could result in an increased cost. "Production Average Speed" and "Effective Area Capacity" is useful when understanding how much ground the machinery is covering. This allows crews to plan how long they have until they finish a field or whether they should start another field.

Peyton (2011) found that the overlap efficiency of a shredder, without precision agriculture, was 95 percent. The efficiency can be increased utilizing precision agriculture and can vary depending on operator skill. Using Equation 2, the effective swath width was found. This, along with production speed, allowed for the calculation of the effective production capacity, Equation 3.

$$w_e = w_t * E_s \qquad \textbf{(2)}$$

Where: w_e = effective swath width, m

w_t = theoretical swath width, m

E_s = swath efficiency, decimal

$$C_e = \frac{sw_e}{10} \qquad \textbf{(3)}$$

Where: C_e = effective capacity, ha h^{-1}

s = field speed, km h^{-1}

w_e = effective swath width, m

Providing a daily summary of productivity allows for managers to analyze whether it is possible to complete the harvest within the given window, or if more resources are needed in order to complete the job or push for higher productivity and longer working hours. These metrics are also useful when understanding how much equipment will be needed for following years in order to complete the harvest within a given time window.

Baler Productivity Metrics

Balers have several more key productivity metrics that are useful in gaining a better understanding of productivity. These additional baler metrics are combined with the general metrics to get a detailed analysis. Balers are very complex and must be more closely managed in order to properly function. If a baler isn't reaching maximum capacity or functioning properly, it results in the whole system being less efficient. Shredders must slow down or stop production if they get too far ahead of the baler, leaving windrows overnight is not a common practice, due to chances of rain and dew making the material damp, which typically take longer to dry out when compared to material that has not been windrowed. Table 4 shows a summary of the baler productivity metrics.

Table 4: Baler Productivity Metric Summary

Metric	Unit of Measurement
5th Bale Production	Time
10th Bale Production	Time
Bales per Production Hour	Bale h^{-1}
Bale count	#
Average Plunges per Flake	Plunges $flake^{-1}$
Average Flake Count	#
Fuel Consumption	L $bale^{-1}$

The 5th and 10th bale production gives a better understanding of the true production start time. When production first starts, crews may be testing the crop to see if it was ready, or making repairs; however, they might not start into production right away. Figure 6 shows an example of median times of production start, 5th bale production, 10th bale production, 15th bale production and 20th bale production. While production started at approximately 11:52, the 5th bale wasn't produced until 12:56

and the 10th bale was produced shortly after at 13:13. This shows that there was delay in production from the time production starts until the time the 5th bale is produced.

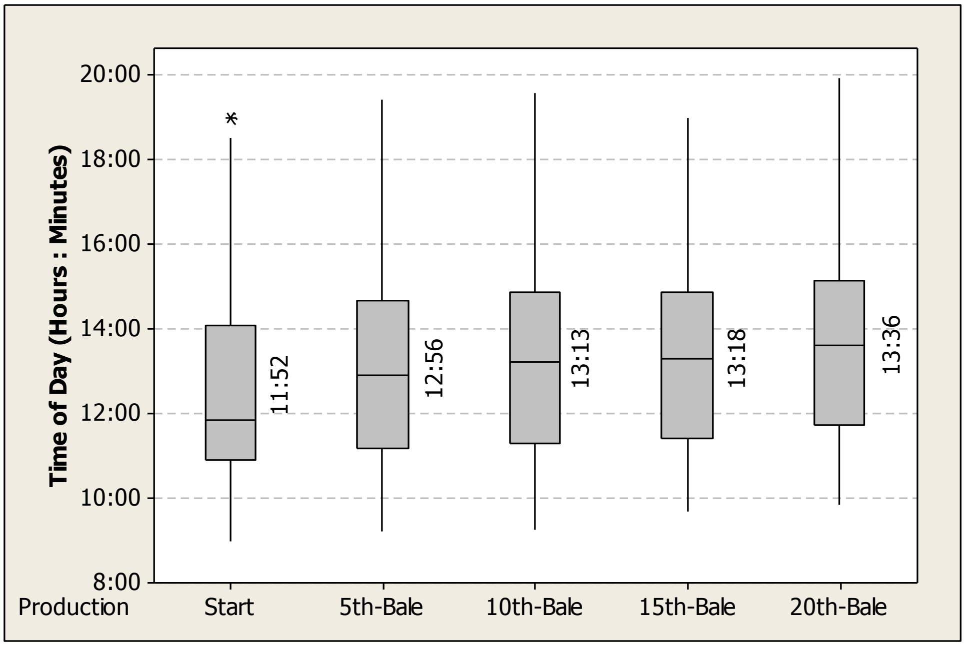

Figure 6: Bale Production Time

Daily bale count was also reported along with how many bales are being produced per production hour. This helps to gain a better understanding of whether crews are having issues, or if production was going smoothly. This also gives an indication of how many bales were produced that need to be transported from fields into storage locations. Average plunges per flake indicates whether the machine is being pushed to 100% of its capacity, a plunge per flake of one means the baler is inserting a new flake every time the plunger makes a stroke. A plunge per flake greater than one indicates that the machine isn't being used as efficient as possible. Both bales per production hour and plunges per flake indicate whether the machine was being pushed while it was in production; while a high throughput is desired, a balance is needed between baler throughput and overall production efficiencies. Pushing the machine to the maximum throughput could result in the baler needing to be repaired more often; while the baler is being repaired it isn't being productive.

Average flake count indicates how many flakes exist in each bale, typically a higher flake count results in higher density and more uniform bales. Fuel consumption is very useful for determining the input costs to make a bale for the supply chain. Both flake count and fuel consumption are calculated as straight averages over the productive period.

Idle Metrics

Idle metrics were useful when looking at how long the tractor was at idle and not being fully utilized. Table 5 shows the metrics associated with idle. This can have a large impact on commercialization; if the machine is at idle for very long periods of the day, the machine may have mechanical malfunctions or an organizational issue may exist. It costs a significant amount of resources not utilizing the machine to its full potential, whether it's due to mechanical or organizational issues.

Table 5: Idle Metric Summary

Metric	Unit of Measurement
Idle Total Duration	h
Idle Fuel Rate	$L\ h^{-1}$

Transportation Metrics

Transportation metrics were useful in understanding the travel time associated with moving from field to field, as well as within the field. Table 6 shows the metrics associated with transportation. Transportation durations should be minimal if the crews have dense field locations and are making adequate decisions on field harvest order. Transportation fuel rates are provided for economic analysis.

Table 6: Transportation Metric Summary

Metric	Unit of Measurement
Road Transportation Duration	h
Road Transportation Fuel Rate	$L\ h^{-1}$
Field Transportation Duration	h
Field Transportation Fuel Rate	$L\ h^{-1}$

Results

2012 Harvest Logistics

Using the metrics obtained in the automated logistics process, targets were generated for areas of improvement in order to produce a cost effective process, while increasing the efficiencies of the supply chain. In the following 2012 summary analysis, only days of productivity over 0.5 hours were used. Harvest of 2012 lasted approximately 50 days from September 11 to October 31; out of the 50 days, 43 days had at least one crew productive for over 0.5 hours.

Shredder Analysis

Shredders are the first process in harvesting corn stover and must be effectively utilized in order to keep the baler productive continuously throughout the day. The following results summarize the 2012 harvest metrics for shredders.

Table 7 below, shows how individual crews utilized the shredder during the day. On average the crews were around the machine for 8.64 hours; out of that, the machine was only running for approximately 75% of the time. The machine could be off for multiple reasons, such as maintaining the equipment or shutting down to wait for the baler to complete the current field prior to moving to the next field. Reducing the amount of time the machine is off increases potential productivity time; however, it is more desirable to have the machine off than the machine on and in idle state. Crew one had a higher crew active duration and also utilized the machine the most with the machine being on for approximately 79% of the time, while crew three had the lowest crew active duration and machine on percentage. There is not enough evidence to suggest that the crew active duration, machine on and machine off means are significantly different from crew to crew at alpha level 0.05; the p-values are 0.301, 0.260 and 0.261, (APPENDIX A).

Table 7: Shredder Crew Active Duration Utilization, Crew averages over entire season and machines

Crew	Crew Active Duration Time (h)	Std. Dev (h)	Machine On (%)	Machine Off (%)
1	9.61	3.16	79.34	20.66
2	8.21	3.93	76.42	23.58
3	8.03	2.75	71.52	28.48
4	8.70	2.65	71.63	28.37
Average	8.64		74.73	25.27

Table 8 shows how the machine was utilized while the machine was on. All crews had similar production duration. The crews have a relatively low idle percentage; however, there was room to decrease this and to increase production. Crew four has the lowest idle at 15.56%, while crew one had the highest at 22.84%. The idle time can be contributed to preparing the shredder for field and transport mode or for maintenance and repairs. The field transportation is kept to a minimum, if the field transportation increases this could be a result of poor field planning by crews or crews having machine breakdowns and needing to return to field edge for maintenance and repair. The road transportation was also minimal and was only likely to improve as the field location density increases. An increase in road transportation would likely be a result of poor planning of the order to harvest fields or that the crew has fields that are spread out. On average, over all crews, only 52.95% of the active duration was spent in production. A one-way ANOVA was done with each of the categories in Table 8 versus the crew; machine on, production and road transportation had p-values of 0.154, 0.835, and 0.669, respectively. At an alpha level of 0.05, there is not enough evidence to suggest that the means are different across the crews (APPENDIX A). There is enough evidence to suggest that idle and field transportation does vary across the crews, applying Tukey's method to determine the crew difference; crew four's mean for idle and field transportation varies from the other three crews

.

Table 8: Shredder Machine On Utilization, Crew averages over entire season and machines. Values that do not share a letter are significantly different

Crew	Machine On Time (h)	Machine On Std. Dev (h)	Production (%)	Idle (%)	Idle Tukey's Method	Field Transportation (%)	Field Transportation Tukey's Method	Road Transportation (%)
1	7.53	2.78	70.97	22.84	A	1.04	A	5.36
2	6.03	2.94	70.54	20.16	A	1.87	A	7.63
3	5.92	2.66	69.88	21.71	A	2.31	A	6.49
4	6.24	2.44	72.03	15.56	B	5.20	B	7.28
Average	6.43		70.86	20.07		2.61		6.69

Analyzing the shredder productivity and idle over the day of year for all crews can be seen in Figure 7. The day of year corresponds to the date out of 365 days (day of year 255 is September 11, 2012 and day of year 305 is October 31, 2012). The circle size indicates how many bales were produced by the crew on that day; a larger diameter circle corresponds to a higher count of bales. It was evident that the crews spent a majority of the time in production while the engine was running and did not seem to improve as the season progressed. The time spent at idle was significantly lower than the production with the exception of a few data points.

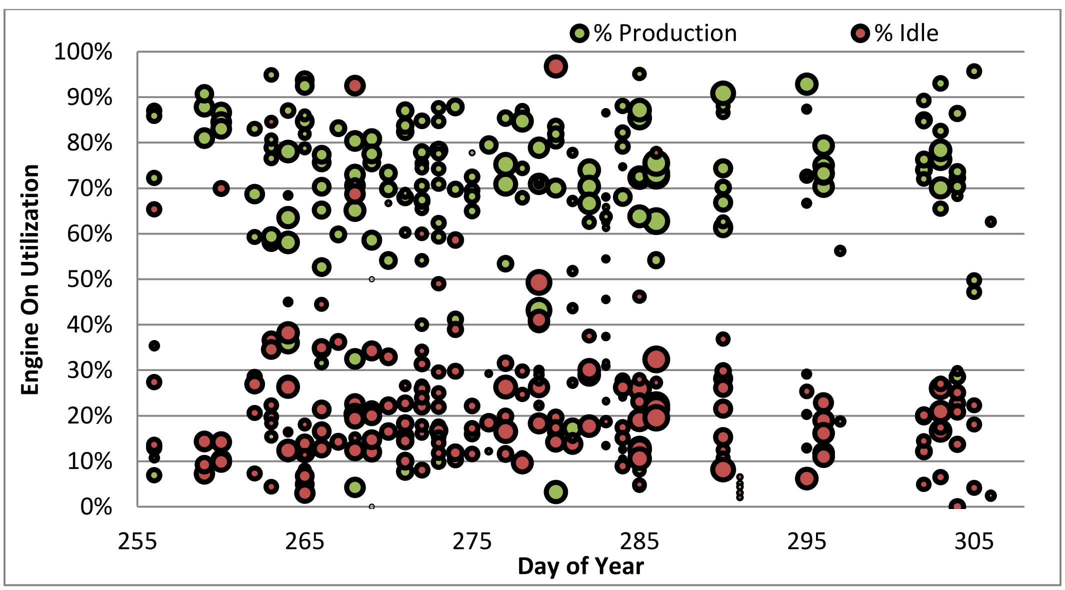

Figure 7: Shredder Engine On Utilization over entire season for all crews

Theoretical area production capacity and effective area production capacity are shown in Table 9. On average, the crews had a theoretical area capacity and effective area capacity of 7.9 ha h⁻

^{1} and 7.5 ha h^{-1}, respectively. Performing a one-way ANOVA for effective capacity, the p-value was 0.026. This suggests that at least two of the four means are significantly different at an alpha level of 0.05. In order to determine which means were significantly different, Tukey's method was used. While crew one and three are significantly different there is not enough evidence to suggest that they are different from crew two and four.

Table 9: Theoretical and Effective Capacity by crew, Values that do not share a letter are significantly different

Crew	Theoretical Area Capacity (ha h^{-1})	Effective Area Capacity (ha h^{-1})	Tukey's Method
1	7.2	6.8	A
2	7.8	7.4	AB
3	8.5	8.1	B
4	8.0	7.6	AB
Average	7.9	7.5	

Figure 8, shows the median production fuel rate and median production ground speed, averaged over the season. On average, over all crews, the median fuel rate and ground speed was 22.3 L h^{-1} and 8 km h^{-1}, respectively. The crews had a similar ground speed while in production, which shows that the crews dialed in an adequate speed for the shredder. The fuel rate fluctuates between crews slightly, which could be a result of field conditions and differences in tractors. Crew one, two and three had the same model tractors however crew four had a different model. This gives a good representation of how much fuel was burned, per hour, while in production, which allows for better supply chain management analysis to reduce costs.

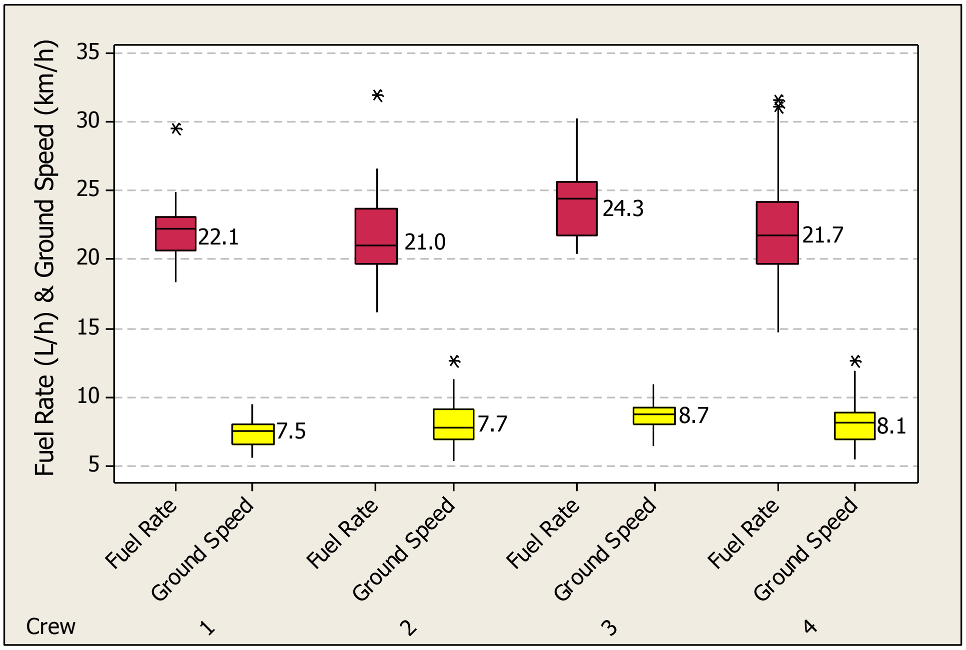

Figure 8: Median Production Fuel Rate (L h^{-1}) and Median Production Ground Speed (km h^{-1}) by crew

Baler Analysis

The crew active duration for balers was 9.73 hours, averaged over all crews for the season; this is an increase of about 1 hour compared to shredder crew active duration. On average, the baler-tractor was on for approximately 69% of the time and off for about 31% of the time. A one-way ANOVA showed that there is not enough evidence to suggest that the crew active duration, machine on and machine off are significantly different at an alpha level 0.05 (APPENDIX B).

Table 10: Baler Crew Active Duration Utilization, Crew averages over entire season and machines

Crew	Crew Active Duration Time (h)	Std. Dev (h)	Machine On (%)	Machine Off (%)
1	9.95	2.58	68.92	31.10
2	9.20	2.93	67.06	32.95
3	9.77	4.41	74.83	25.17
4	9.98	2.54	65.51	34.48
Average	9.73		69.08	30.92

The baler engine on utilization can be seen in Table 11. Production averaged 48%, with a range from nearly 41%, for crew two, to nearly 58%, for crew four. Idle time averaged 42%. Two of the four crews had more time spent in idle than in actual production; on a commercial scale, this must be carefully monitored and adjusted in order to increase productivity. Field transportation and road transportation were kept to a minimum with an average of 3.5% and 7.0%, respectively. On average, only 33% of the crew active duration was spent in production. This shows that adjustments can be made in order to increase the baler productivity to more acceptable levels for commercial harvest applications. A statistical analysis was performed on each category in Table 11; there was not enough evidence to suggest that the machine on mean values were different across the crews. While crew one and two are not significantly different from one another, they are both significantly different from crew three and four, which are significantly different from each other, in both production and idle. There was also significant difference between the crews in field transportation and road transportation (APPENDIX B).

Table 11: Baler Machine On Utilization, Crew averages over entire season and machines, Values that do not share a letter are significantly different

Crew	**Machine On**		**Production**		**Idle**		**Field Transportation**		**Road Transportation**	
	Time (h)	Std. Dev (h)	(%)	Tukey's Method	(%)	Tukey's Method	(%)	Tukey's Method	(%)	Tukey's Method
1	6.72	2.26	42.18	A	49.29	A	4.20	A	4.34	A
2	5.98	2.47	40.96	A	48.36	A	3.93	A	6.81	AB
3	6.79	3.08	50.87	B	38.54	B	3.53	AB	7.06	AB
4	6.50	2.21	57.63	C	30.34	C	2.46	B	9.60	B
Average	6.50		47.91		41.63		3.53		6.95	

Figure 9 shows the baler analysis for crew one. The day of year corresponds to the date out of 365 days (day of year 255 is September 11, 2012 and day of year 305 is October 31, 2012). The diameter of the circles correspond to the amount of bales produced on that day, a bigger diameter represents more bales produced that day. It was evident that production and idle was very much intermixed, this is very undesirable. If this information was available and tracked during the harvest season on a daily basis process, enhancements could increase productivity and decrease inefficiencies in the machine or organizational strategy.

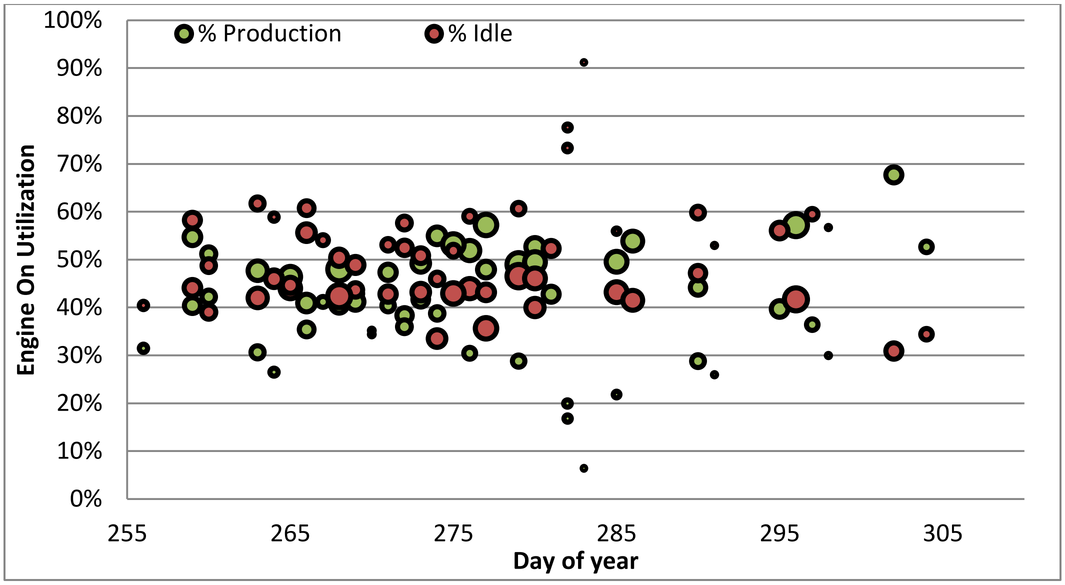

Figure 9: Baler Engine On Utilization for crew one by day of year

Figure 10 shows the baler analysis for crew two. It was evident that the majority of time spent at idle exceeds the time for production. This shows that the crew has either organizational or mechanical issues that need resolution. This was very undesirable, and it increases the cost to produce bales, and increase the time window needed to complete harvest. The utilization for the machine while the engine was running averaged 41% in production and 48% idle. This tool allows for daily reports to be generated, if this high idle time was flagged in the first couple days of harvest, the crew could have made changes in order to increase productivity and decrease idle time, increasing productivity earlier on would have potentially decreased the harvest days from 50 to the target of 30. This will drive key management decisions in order to be highly productive within a short harvest window.

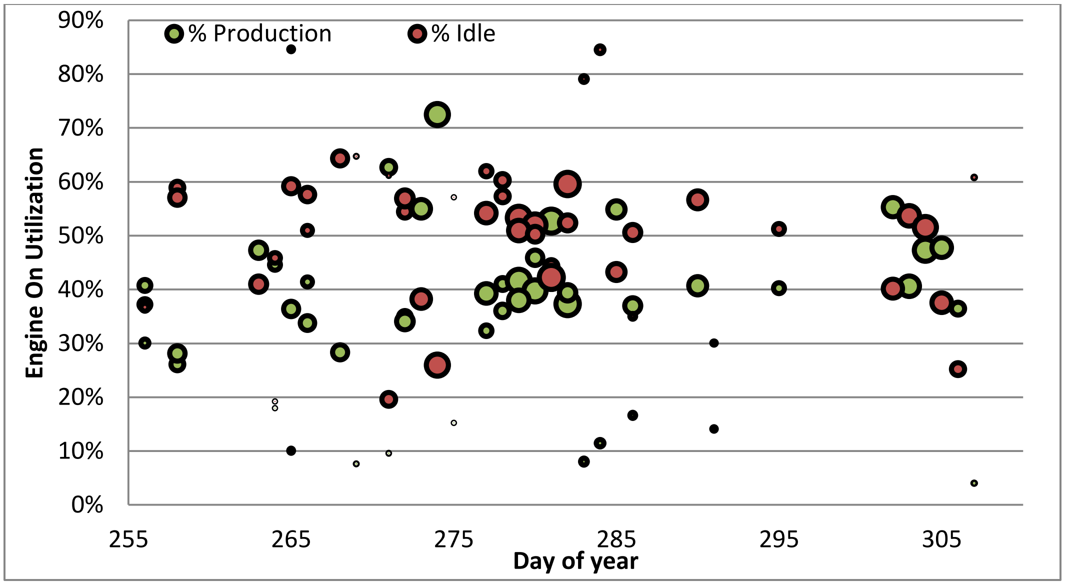

Figure 10: Baler Engine On Utilization for crew two by day of year

Figure 11 shows the baler analysis for crew three. It was evident that the crew has a slightly higher production than idle time. This would suggest that the crew was better organized and avoided mechanical downtime. However it also shows that there was room to improve the production to a higher percentage while decreasing the idle duration.

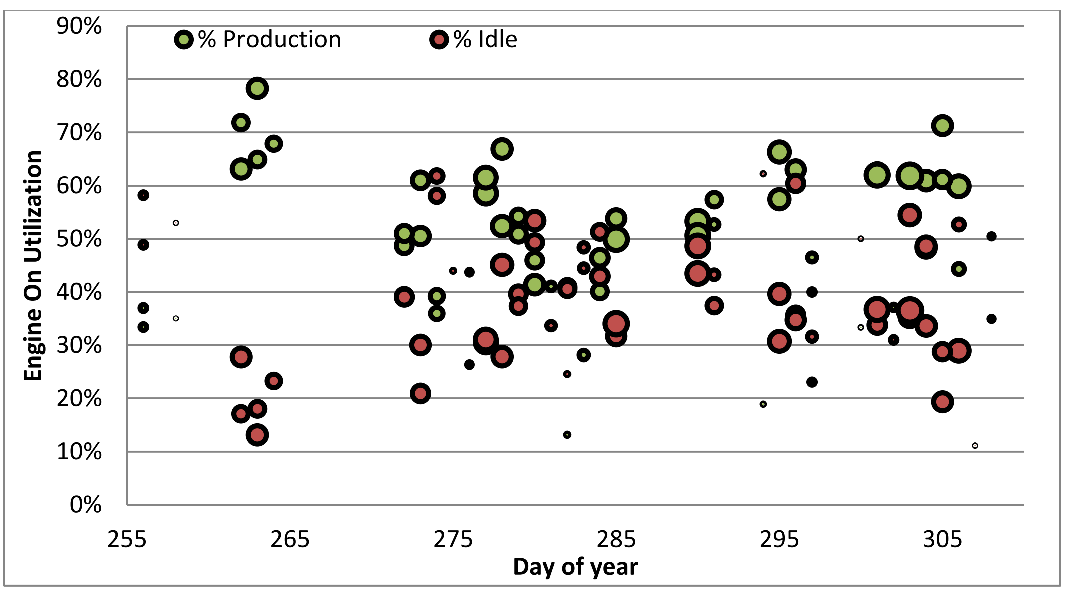

Figure 11: Baler Engine On Utilization for crew three by day of year

Baler analysis over the entire season can be seen in Figure 12 for crew four. Trends show evidence that production and idle are stacked so that the production was larger than the idle time which would be desirable in order to maintain efficiencies. With the ability to obtain these results on a daily basis, supply chain managers could have approached crew four to understand what tactics were being utilizing to have a high productivity. The supply chain managers could have applied these tactics and worked with the other three crews to increase their productivity.

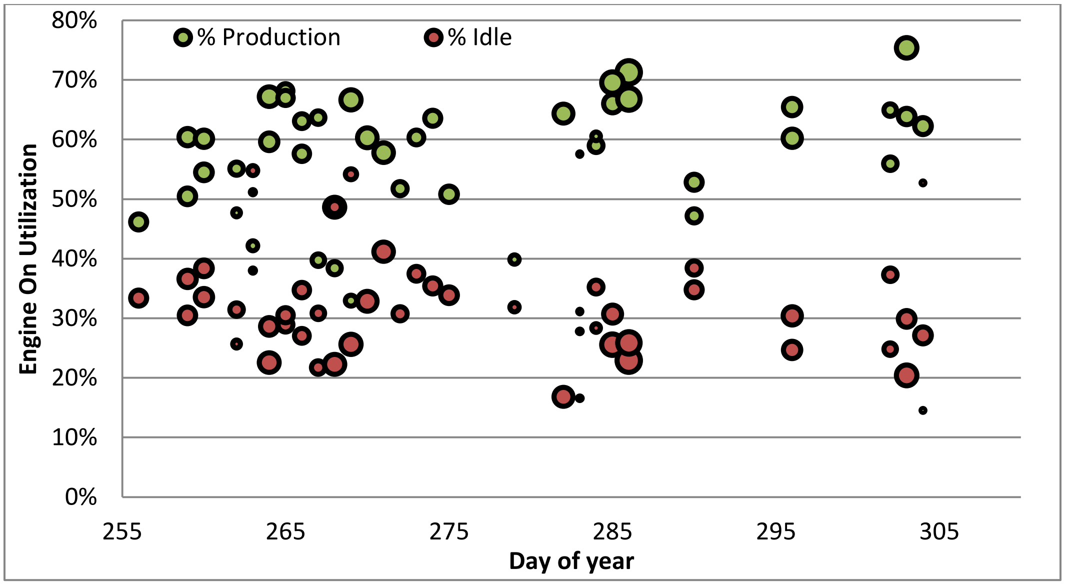

Figure 12: Baler Engine On Utilization for crew four by day of year

Table 12 shows the baler productivity for the four crews averaged over the season. The average effective area capacity is approximately 13.2 ha h^{-1} with crew one having the lowest capacity and crew four having the highest, with a difference of about 4 ha h^{-1}. Crew four also had the highest bales per day, while crew two had the lowest, and the total supply chain averaged 189 bales per day per crew, or a total average of 756 bales per day. The crews have a similar flake count and bales per hour which would suggest that the baler has an average production limit around 60 bales per hour. A one-way ANOVA was performed for all the categories in Table 12; if there was significant evidence to suggest that the mean was different across the crews, further analysis was performed to see which ones differed. Effective area capacity is similar across crew one, two and three; however, there is evidence to suggest crew four has a significantly different capacity. While there is not enough evidence to suggest that the bales per hour are different across the crew, there is sufficient evidence to suggest that the bales per day across the crews are different (APPENDIX B).

Table 12: Baler Productivity seasonal average by crew, Values that do not share a letter are significantly different

Crew	Effective Area Capacity		Bales per day		Flakes per bale		Bales per hour	Fuel consumption	
	(ha h^{-1})	Tukey's Method	(bale day^{-1})	Tukey's Method	(Flake day^{-1})	Tukey's Method		(L $Bale^{-1}$)	Tukey's Method
1	11.74	A	181	AB	36	AB	59	0.59	A
2	12.84	A	146	B	36	A	58	0.61	A
3	12.19	A	207	A	40	BC	57	0.62	A
4	15.94	B	222	A	41	C	58	0.73	B
Average	13.18		189		38		58	0.64	

Figure 13 shows a comparison of the production start, 5th bale production and 10th bale production, the median value is shown. Crew four had the most precise start time with an interquartile range of 1.2 hours, the next precise crew had an interquartile range of 3.2 hours. However, the median production start time is 11:18 with 5th and 10th bale production slightly following the start of production. The late start time in production raises concerns on why the balers can't start at an earlier time such as 8:00. It is possible that the balers were waiting on the shredders to produce windrows, maintaining and repairing machinery, or waiting for dew to evaporate. These inefficiencies can be corrected, and the production start time can be decreased to an earlier start time in order to have a more productive day. Crews one and two also have a significant time gap between when production started and the 5th bale was produced; this suggests that the crews were performing maintenance on the machines or making repairs.

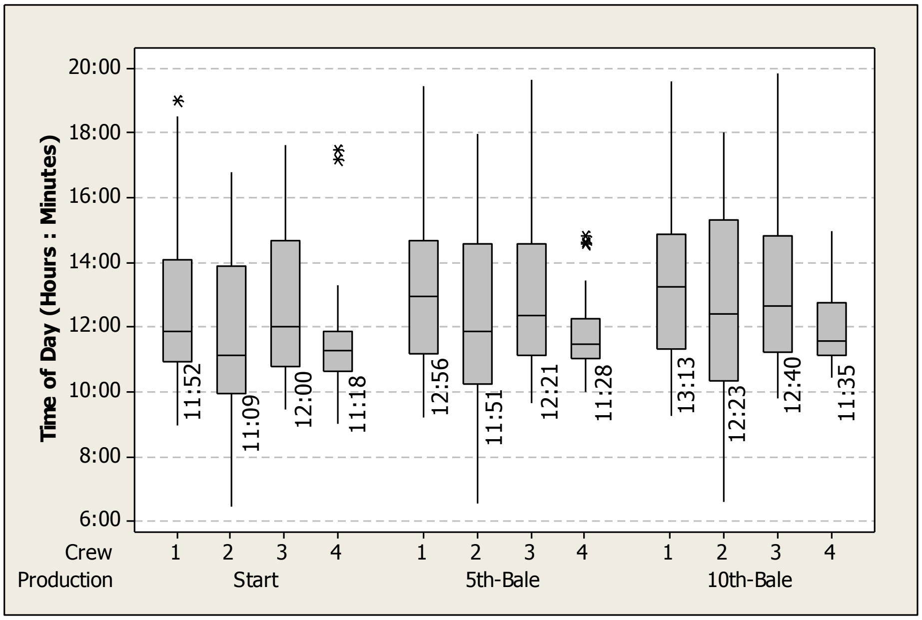

Figure 13: Crew comparisons of Baler production start, 5th bale production and 10th bale production times

2012 vs 2013 Harvest Logistics

In 2013, harvest lasted 72 days, which started September 26 and ended December 6, 56 of these days had at least one crew productive for over 0.5 hours. In 2013, 24,300 hectares were harvested; based on the results from 2012, it would take approximately 3,240 hours of shredder productivity, or about 713 days of harvest for one machine. With a target harvest window of 30 days, approximately 24 shredders would be needed to be productive every day for at least 4.5 hours. Approximately 1,940 hours of baler productivity would be needed, or about 623 days of harvest for one machine, with a crew active duration of 8.64 hours. Given the same harvest window, approximately 21 balers would be needed to be productive every day for at least 3.1 hours, with a crew active duration of 9.73 hours. This does not include that the fields aren't always ready to be harvested right when the crews are ready, nor account for rain events.

During 2013 harvest, all crews had direct access to these performance metrics to drive crew and machinery improvements. Daily reports were generated for crews with a metric summary for each implement type; baler and shredder. These generated reports were also available to supply chain managers and machine technicians. The crews were able to see where they ranked in the supply chain versus other crews, to motivate for an increase in productivity and efficiencies. These metrics provided adequate informative feedback that allowed for direct supply chain improvements.

Table 13, below, shows the difference from 2012 harvest and 2013 harvest with shredders. The percentages in production dropped slightly by 3% points in 2013, although idle remained about the same and transportation rose by 5.5% points compared to 2012. The drop in production is rather minimal for how much transportation increased, the rise in transportation is due to an increase in the supply radius and larger average distances between fields. Performing a statistical analysis, there is sufficient evidence to suggest that the mean production, transportation and productivity of crew active duration are significantly different across the years at an alpha of 0.05 (APPENDIX C).

Table 13: Shredder comparison 2012 vs 2013, averaged across all crews

	Crew Active Duration	**Machine On**		**Productio n**	**Idle**	**Transportation**	**Productivity out of Crew Active Duration**
	(h)	(%)	(h)	(%)	(%)	(%)	(%)
2012	8.57	73.94	6.34	71.28	18.23	10.64	53.46
2013	8.48	71.01	6.02	67.29	18.20	16.16	48.37
Difference	-0.09	-2.93	-0.32	-3.39	-0.03	5.52	-5.09

Table 14 shows the difference from 2012 to 2013 in baler production. The key improvements are a rise in productivity of 8% points and a fall in idle of approximately the same amount. This increase, a result of better management, put baler productivity at 56% for 2013. By having direct feedback of how the machines were being utilized, crews were able to adjust practices in order to optimize efficiencies and decrease downtime. At an alpha level of 0.05, there is enough evidence to suggest that the means from 2012 and 2013 are different for production, idle, and production out of crew active duration (APPENDIX D).

Table 14: Baler comparison 2012 vs 2013, averaged across all crews

	Crew Active Duration	Machine On		Productio n	Idle	Transportation	Productivity out of Crew Active Duration
	(h)	(%)	(h)	(%)	(%)	(%)	(%)
2012	9.74	69.05	6.73	48.29	41.21	10.53	33.69
2013	9.50	70.81	6.73	55.96	32.90	11.78	40.04
Difference	-0.24	1.76	0.00	7.67	-8.31	1.25	6.35

Conclusion

This automated approach can be used to analyze machine data, allowing for determination of machinery and crew performance. This allows management and machinery adjustments to be made in order to increase productivity and efficiency. While 2012 data was collected at the end of the year, this automation allows for data to be collected daily and analyzed in order to adjust the performance of the machines or crews. Having a tool that accurately provides informative feedback in a commercial harvest is crucial when hundreds of machines are being used. It is impractical to personally monitor the crews and provide a daily feedback in a timely manner. The 2012 data shows that there is a significant improvement that can be made in both the shredder and baler productivity; having daily summary information will help to improve each crew earlier in the season. This tool allows for feedback to help the crew gain knowledge on maintenance and organizational issues that exists and allows for a direct comparison of crews. The entire harvest operation can be evaluated on a daily basis to ensure that quality and productivity is reaching acceptable levels for a large biomass chain supply.

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CHAPTER 3. AUTOMATED DOWNTIME ANALYSIS OF GIS DATA FOR AGRICULTURAL HARVEST EQUIPMENT

Abstract

Technological advancements in agriculture allow for data to be mined and analyzed by accessing the controller-area-network (CAN) bus. Equipment such as the large square baler are considered "smart" in the sense that they connect the operator to what is happening on the machine via the implement bus. These complex machines alert the operator when something has occurred that affects the normal operational flow, such as a shear bolt failing. The operator is then alerted of the malfunction via the virtual terminal and can fix the problem to prevent the baler from being damaged, as well as continue to produce a desirable end product at a high productivity rate. Capturing and analyzing these alert messages on the implement bus allows for downtime assessments of what is occurring on the baler, allowing for better equipment management and understanding of root cause downtime.

The main objective of this study was to automate the downtime analysis of large square balers to determine the main root causes of infield malfunctions. The root causes can then be assessed to determine how productivity and performance are affected for each individual malfunction. This allows for better machine management and provides an area of focus for technicians, trainers, engineers, and managers to hone in on key root cause downtime to increase productivity. Machine data was obtained during a large commercial production harvest of corn stover during the falls of 2012 and 2013. In 2013 approximately 800 hours of productivity was lost due to maintaining the baler during the five mechanical malfunctions. Approximately 46% of the baler idle time in 2012 was contributed to five mechanical malfunctions that occurred during normal baling operations. These instant downtime metrics, such as productivity loss and idle time, will drive overall supply chain evaluation of key baler downtime.

Introduction

While the previous chapter focused on the automation of logistics, this chapter described investigations to understand the downtime of the machinery. Integrating this knowledge with the previous logistics allows for instant mechanical performance assessments of the harvest equipment. Understanding why downtime is occurring allows for adjustments to be made both mechanically and organizationally. Large square balers are the primary focus, because the baler sets the productivity for itself as well as the shredder and contains a very complex system. In 2012, the average baler production was 48% and the average idle was 41% for all crews while the engine was running, and only 34% production during the entire day. Current large square balers are also “smart” in the sense that they are electronically tied into the tractor via the implement bus. When sensors are tripped on the baler, a message is sent across the bus to alert the operator that something has occurred; each sensor sends a unique signal within a specific message to the virtual terminal. The messages can be captured and the signals analyzed in order to track which ones are occurring and how often. This allows mechanics or engineers to further analyze the malfunction to reduce the time it takes to maintain the baler, the number of time the events occur, or eliminate the downtime all together.

Balers are mechanically designed to flow material smoothly from the time material is picked up from the ground until the time it is compressed into a bale and dropped on the ground. With the complex mechanical system, several problems are possible. In order to economically bale, first a windrow of material is gathered; a windrow is material that is brought together from a wider distance and condensed down into a narrow row of material that is just wide enough for the baler to pick up.

Figure 14: Side discharge shredder creating windrow

The baler uses curved teeth to carry the material off the ground and into the baler. Sometimes a “slug” of material flows through the pickup, which causes the pickup to slow or even stop. A “slug” of material is a common term used to describe a large pile of clumped material; this is due to the windrow not being uniform. When this occurs severely, the pickup must be physically cleaned out before it will be operational again. Slowing down ground speed or stopping will also allow the material to be fed through, if the plug is minimal. The pickup also tends to slip once the stuffer shear bolt fails, which disrupts the flow of material through the baler, and the incoming material has nowhere to go except to plug or jam the pickup. The stuffer is the mechanical system that moves a new flake into the bale chamber. A flake is first formed in the pre-compression chamber by packer fingers, which is important in order to produce a uniform bale and begin the density transformation. If the flake requires too much force when moving into the bale chamber, a stuffer shear bolt breaks. This is typically due to an increase in friction between the stuffer walls and the material; soil and moisture have an impact on material friction, as well as the uniformity of the material.

Once the flake is inserted into the bale chamber, the plunger strikes the flake and pushes it back into the bale chamber, where it is compressed due to downstream friction and forces resisting bale movement. To maximize machine throughput, a one-to-one ratio of plunges to flakes being inserted is desirable. The bale chamber is adjustable by hydraulic cylinders; the cylinders create pressure on the bale from all sides. When the pressure is increased, the friction increases between the bale and the chamber walls. The added friction increases the force needed to move the bale throughout the chamber. This creates the back force on the flake that is inserted and results in the flakes being compressed. Higher chamber pressures result in a denser bale. Flake size is also important when trying to produce high density bales; typically the smaller the thickness of the flake, the denser the bale will be. Flake size also has an impact on the force exerted on twine strands; a bale with the lesser flake count will put more stress on twine strands. Once approximately 35-55 flakes have been compressed together, they create a bale. The compressed bale is held together by means of synthetic twine.

The twine is mechanically tied, by means of a knotter; each twine strand contains two knots, and each bale contains six twine strands. The twine strands are evenly spaced among the bale in order to secure the bale without breaking. Thus, each bale contains 12 knots; every time a knot is made, a complex mechanical system must work perfectly without any environmental interference. The knotter cycles twice in a row, in less than a second, producing the last 6 knots of the bale just made and producing the first 6 knots of the next bale to be made. Once the bale has been secured with twine, the bale gets pushed out the back of the baler as more material is fed into the baler. Once the bale has cleared the bale chamber it gently slides off of the baler tailboard.

Having knowledge of how a baler operates and the mechanical issues that occur during harvesting allows an analysis of the baler signals to determine the main cause and downtime of mechanical instances. This allows organizational downtime and mechanical downtime to be separated, machine technicians to be dispatched to crews having mechanical problems, and other resources to be dispatched to aid in the organizational issues. Organizational issues are easily corrected by applying time management skills, while mechanical malfunctions might require repairing the equipment or “dialing in” certain components to operate the most effectively. “Dialing in” is referred to as making small adjustments to the mechanical system to run the machine at its best performance settings, while all balers are mechanically similar each baler has a unique best performance setting. Balers must also be re-adjusted as the season progresses; since the mechanical components will wear with use.

Research Objective

The objective of this project was to develop automated downtime analysis of GIS data for the determination of root cause of in-field issues. Allowing for downtime instances to be classified into either major machinery malfunctions or organizational logistic issues.

Materials

Data Logging Instrument

Machine data in 2012 was captured using CyCAN loggers developed by Matt Darr at Iowa State University in Ames, Iowa. The logger software filtered for specific parameter group numbers (PGN) on the implement bus. The J1939 standard (SAE, 2013) was used to determine which PGN numbers were desired, based on the signals contained within that specific message. CyCAN also contained serial ports that utilized the RS-232 protocol to capture GPS information, such as date, time and global coordinates. Data was recorded at one second intervals when the tractor was keyed on and the data was saved to a memory disk. The data was collected at the end of the harvest season to be analyzed. Multiple machine parameters were recorded, such as tractor engine speed, vehicle ground speed, global coordinates, PTO speed, bale counter, fuel rate, date and time.

Harvest data for 2013 was captured using a second generation telemetry logger, similar device to the CyCAN logger in the way it captures information; however, the logger device had the capability of performing onboard calculations such as real time productivity and to transmit data through telematics. Telemetry supports data transfer wirelessly via a cellular network much like cellphone communication today. This allowed data to be captured, analyzed and sent to managers remotely. The data was down sampled at 15 second intervals compared to the previous logging of one second. Powell et. al. (2013) reported that down sampling to collect data every 15 seconds had minimal impact on productivity calculations.

Equipment Used

In 2012, Hiniker 20 foot side discharge shredders (model 5620) were utilized to chop the stalks and to simultaneously create windrows of material for the balers to pick up. In 2013, the shredders used were Hinker model 5620HH, which work the same as the 2012 model however had an additional feature. In 2013 a hydraulic swinging tongue was added to easily transition between transportation mode and field mode. Shredders, in both 2012 and 2013, were driven with tractors that had at least 225 horsepower output at the PTO.

Three crews in 2012 utilized AGCO's large square baler (model LB34B XD), which produced bales 3 ft. by 4 ft. wide and 8 ft. long. Crew four utilized Krone large square balers which produced a bale the same size as the AGCO baler. In 2013 all crews used AGCO large square balers. Balers, in both 2012 and 2013, were driven with tractors that had at least 300 horsepower output at the PTO. In the following analysis, only data from AGCO balers was utilized.

Harvest Logistics Raw Data Set

During the corn stover harvest in the fall of 2012 in Iowa, a data logging instrument, CyCAN, was installed on ten shredders and nine balers across four different crews that harvested a total of 6,000 hectares and produced approximately 37,000 bales. Over 2,800 hours of CAN and serial data was captured and recorded from these 19 machines, within a harvest window of 50 days. Each of the four crews had a work area around central Iowa and was assigned fields as the grain harvest was completed. The crews were tasked with windrowing the stover, baling, and producing a field edge stack, which would be later moved by other means.

During the harvest of fall 2013 in Iowa, a second generation telemetry system was installed on over 100 machines that harvested approximately 24,300 hectares and produced over 172,800 bales. The second generation telemetry system contained all the features and capabilities of CyCAN, plus several additional features. The logging device utilized telematics to transmit data every 15 seconds to a server, where the data was stored, analyzed, and reports were automatically generated and then emailed out to certain individuals. The logging device also had the capability of performing onboard calculations such as real time productivity. Ten crews were utilized to collect, densify and stack the corn stover at field edge. In 2013, harvest lasted 72 days, which started September 26 and ended December 6; 56 of these days had at least one crew productive for over 0.5 hours.

Methods

Baler Implement Bus Message

Modern day balers communicate with the operator in the tractor cab through the implement bus, specific baler signals are sent from the baler to the virtual terminal (VT) display within the tractor cab. This display allows the operator to monitor and control specific functions of the baler. If certain sensors change status on the baler, there is a message that is sent to the VT to alert the operator. Baler mechanical signals sent across the VT were recorded in the fall of 2012. The signals that were captured are proprietary and are not included in the J1939 standard; this made it difficult to link specific signals with what was occurring. In the summer of 2013, the messages were decoded in order to link a specific CAN signal to what was occurring on the baler. Figure 15 shows the signals that were recorded and how many of each occurred during the harvest. It was evident that certain failure modes occurred more frequently than others.

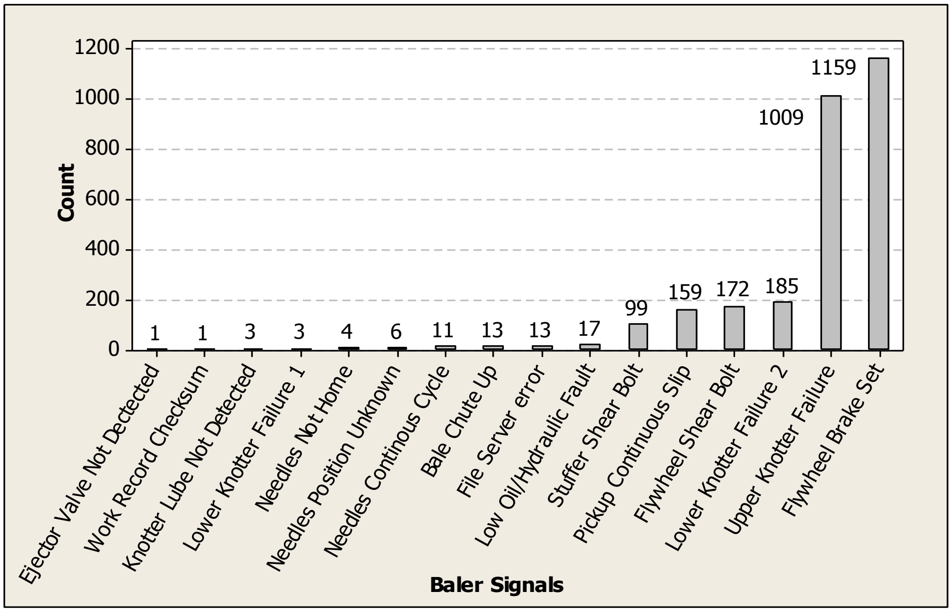

Figure 15: Complete Baler Signals from 2012 Harvest

The top six signals were selected for further analysis; these signals occurred more often than the rest and have a greater impact on productivity and downtime. Out of the six signals captured, five help to determine what mechanical malfunction was occurring with the baler. The "Flywheel Brake Set" is a brake that is applied to the flywheel of the baler; this stops the mechanical motion of the baler, and locks the rotating unit from freely moving while the machine is being properly maintained or repaired. When maintaining equipment, the tractor should always be powered off and the flywheel brake should be applied. This reduces the risks associated with working on the mechanical systems.

The baler signal "Stuffer Shear Bolt" occurs when the forces exceeds the shear bolt strength; the shear bolt allows the stuffer to mechanically move a flake of material into the bale chamber. Once the shear bolt breaks, the stuffer no longer has a means of moving. The bale signal "Flywheel Shear Bolt" occurs when the bolt connecting the PTO to the baler flywheel shears; this is a safety mechanism to protect the entire baler from being damaged when the demanded torque out succeeds the torque the baler is capable of handling.

The baler signal "Pickup Continuous Slip" occurs when the baler pickup clutch is slipping. This typically occurs when a slug of material passes into the pickup and plugs up the throat going into the stuffer chamber. This can also occur if the stuffer shear bolt fails and backs up the flow of material going into the bale chamber. The baler signal "Lower Knotter Failure 2" occurs when the twine slacker arm becomes loose; this is typically due to the twine breaking and allowing the arm to release tension. The signal "Upper Knotter Failure" occurs when the knotter misties, allowing the slacker arm to become loose. The twine typically gets cut and will no longer function properly, this can cause damage to the knotter and leads to loose strings in the field.

If any of the five signals occur, it is recommended to stop production immediately to correct the malfunction. Not fixing the issue can result in the baler being significantly damaged and result in a longer maintenance time.

Baler Mechanical Downtime Analysis

Baler mechanical downtime was analyzed in several different ways; Figure 16 shows the basic approach of the analysis. This approach identified when a baler signal is sent, and if the machine goes from production state to idle state, the time is captured. This time is then compared to when production starts back up. This approach was also expanded to include capturing time when the baler signal happens after production has ended; some instances will result in the operator catching the failure prior to the baler system. For example, an instance would be when the twine wraps around the knotter system, and the twine holds the slacker arm from coming up, the operator can catch that the flag on the slacker arm isn't moving and can correct the problem, upon fixing the problem the slacker arm tension is released and the sensor is then tripped.

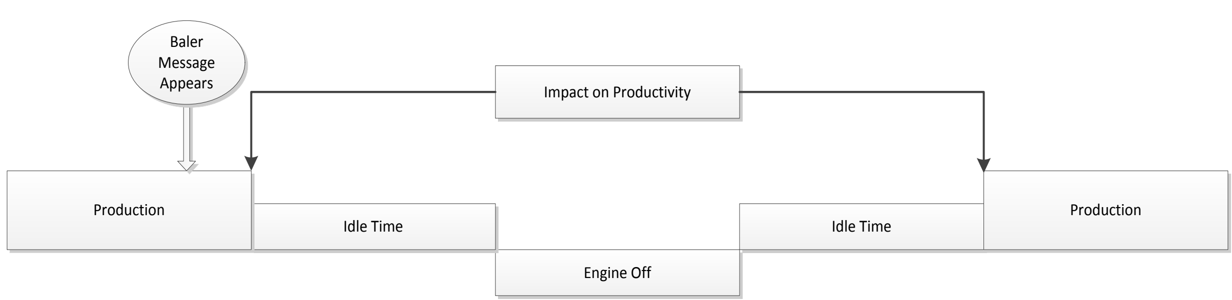

Figure 16: Approach for Production Loss and Idle Due to Baler Mechanical malfunctions

This analysis allows for several key metrics to be determined, including productivity loss and idle time (Table 15). Productivity loss was determined to be any non-productive time where an event occurred, whether the baler-tractor was idling or the engine was shut off. Event idle time was the amount of time spent idling, due to the event. These events were classified in order to analyze by each type of baler mechanical signal. This produced an expected productivity loss and expected idle time for each signal. Baler malfunctions per day and bales per baler malfunction, alerts how often individual events are occurring. A low number of baler malfunctions per day is desired, while a high bales per baler malfunctions is desired.

Table 15: Baler Downtime Metric Summary

Metric	Unit of Measurement
Baler Malfunctions per Day	#
Bales per Baler Malfunction	#
Event Productivity Loss	Time (min, h)
Event Idle time	Time (min, h)

Results

Figure 17 shows the signals of focus for the 2012 and 2013 harvest. The "Upper Knotter Failure" signal occurred the most, at 1,009 times during 2012, and 2,953 times in 2013. This is a very significant mechanical failure compared to the next failure of "Lower Knotter Failure 2," which occurred 185 times in 2012, and 733 times in 2013. Having a mechanical fault with the knotter system typically results in the twine not being tied properly, which leads to loose twines throughout the field and also results in a weaker bale. Once a bale loses a twine strand, it leads to more pressure and stress on the remaining strands; this can cause all strands to break when the bale is handled. The bale then has to be spread out and re-baled, which decreases productivity. The strand, if not picked up, remains in the field and doesn't disintegrate over time; this causes issues when the field is tilled or planted, the twine wraps up around parts of the equipment, causing it to not function properly.

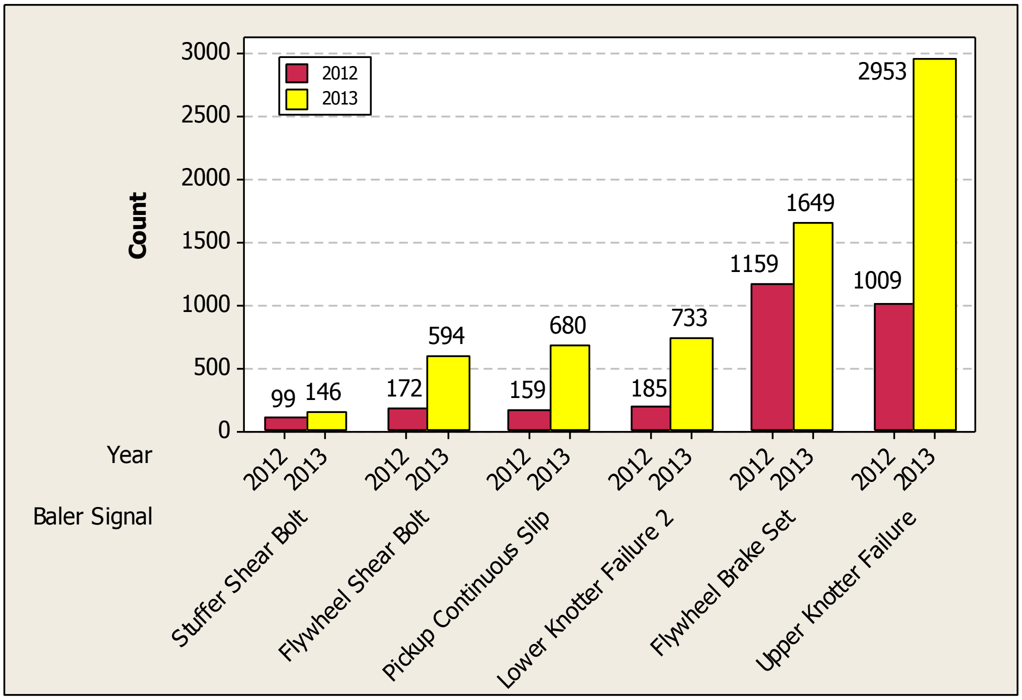

Figure 17: Baler Signal Comparison 2012 and 2013

Mechanical Malfunctions

In total, 2012 total baler mechanical signals was 1,624; this equates to 22 bales per mechanical malfunction (Table 16). The crews had a similar amount of baler malfunctions occurring per day; however crew two had more malfunctions per bale compared to crew one and three.

Table 16: Average Bale malfunctions per day and bales per baler malfunction by crew for 2012, note crew four used different balers and data is not available

Crew	Baler malfunction per day	Bales per baler malfunction
1	10	24
2	11	18
3	10	23
4	*	*
Average	10	22

An expected value for how many bales are produced until baler downtime occurs can be founded. The data is lognormal distributed, as shown in Figure 19, knowing the location and scale parameters of a lognormal distribution the expected value can be calculated. Equation 4 shows how the expected value can be calculated, and Equation 5 shows how the standard deviation can be calculated. Both equations can be applied to the signals in order to calculate the expected bales per malfunction by signal and the standard deviation by each individual signal.

$$E[X] = e^{\mu + \frac{1}{2}\sigma^2} \tag{4}$$

Where: E[X] = Expected Value of X

μ = Location Parameter

σ = Scale Parameter

$$S.D.[X] = \sqrt{(e^{\sigma^2} - 1) * E[X]^2} \tag{5}$$

Where: S.D. [X] = Standard Deviation of X

σ = Scale Parameter

E[X] = Expected Value of X

Based on 2012 data it is expected that every 21 bales a malfunction will occur from the five signals resulting in downtime, with a standard deviation of 5 bales per malfunction. This follows closely which was founded in Table 16 that the crews averaged 22 bales per malfunction. In 2013, the expected bales per malfunction was 43, this is double the previous year. This suggests that the crews maintained the equipment more closely and also dialed in the equipment during harvesting. Having more bales being produced per malfunction directly helped to decrease the downtime from 2012 to 2013, while increasing the productivity of the crew.

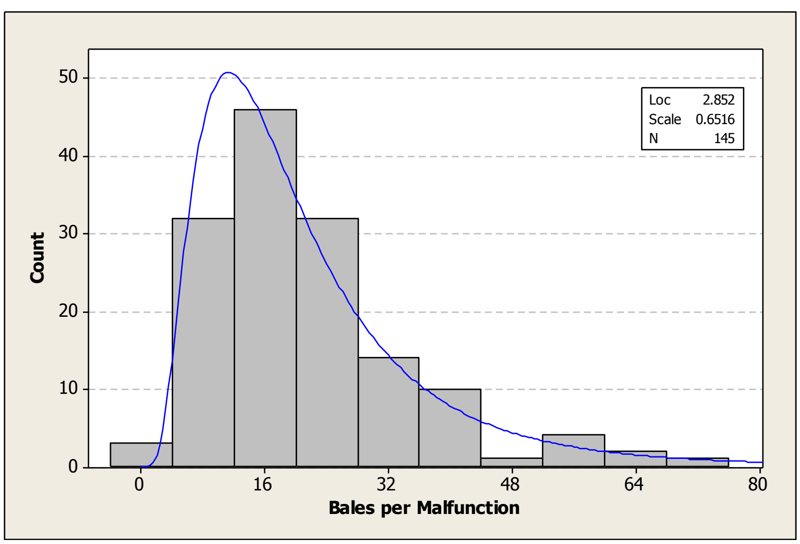

Figure 18: Lognormal distribution for expected bales per malfunction, 2012

Further breaking down the data, an expected value for each malfunction can be founded in order to know how often each signal is likely to occur. The lognormal distribution fits all five signals. The closer the correlation coefficient is to one the better the distribution fits the data. Table 17 shows the resulting expected bales per malfunction by baler signal. The upper knotter failure is expected to occur every 40 bales, while the stuffer shear bolt is expected to occur the least at 165 bales per event for 2012. In 2013, the upper knotter failure, expected bales per malfunction, is 76 compared to the stuffer shear bolt of 193 bales per malfunction.

Table 17: Expected Bales per Malfunction by baler signal for 2012

Malfunction	Year	Location (μ)	Scale (σ)	Correlation Coefficient	N	Expected Bales per Malfunction	Standard Deviation
Flywheel Shear bolt	2012	4.496	0.7593	0.992	74	120	14
	2013	4.314	1.325	0.926	246	180	41
Lower Knotter Failure 2	2012	4.683	0.7498	0.986	91	143	15
	2013	4.529	0.9979	0.977	269	152	23
Pickup Continuous Slip	2012	4.615	0.8976	0.984	77	151	19
	2013	4.383	1.23	0.938	292	171	35
Stuffer Shear Bolt	2012	4.609	0.9985	0.959	50	165	24
	2013	4.418	1.299	0.952	59	193	41
Upper Knotter Failure	2012	3.407	0.7449	0.991	140	40	8
	2013	1.162	554	0.948	554	76	21

With the knowledge unlocked of how often the baler downtime is occurring, this allows for accurate supply chain modeling and resource allocations. However, the next question is to be answered is what time is associated with each downtime and how does this affect overall productivity. This can be extracted based on the machine going into an idle event, and a baler mechanical signal occurring shortly before the idle event occurs, or during the idle event.

Productivity Loss

Productivity loss varies from each individual signal even if it's the same mechanical part. This is due to variability of the machine and of the biomass being baled. The variance and outliers in productivity loss is due to the severity of the issue, depending on how the event was caused results in the productivity loss being greater or lesser. This results in the productivity loss having a lognormal distribution, due to a fixed lower limit and an infinite upper limit. Figure 18 shows a lognormal distribution fit, with correlation coefficients, for the five baler signals for both years.

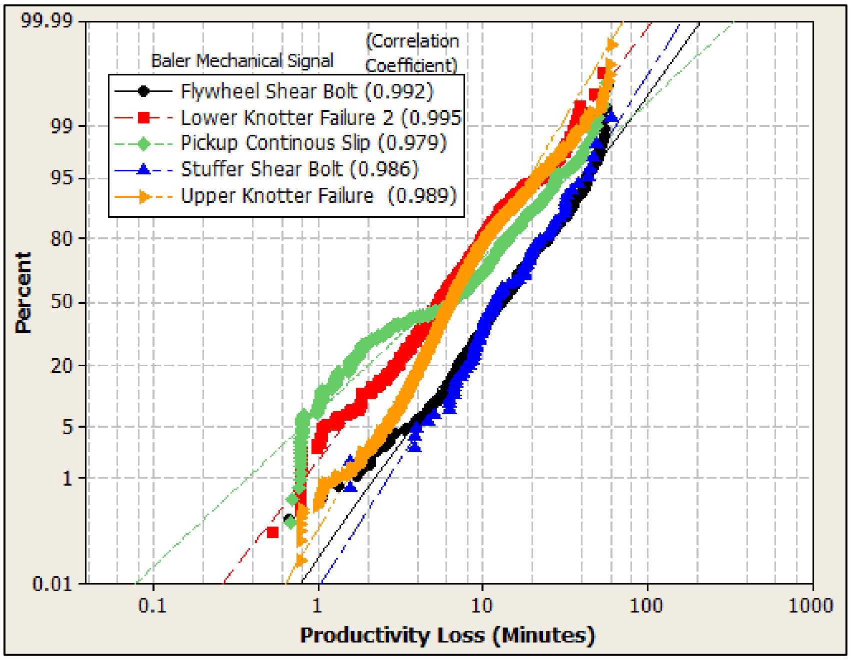

Figure 19: Lognormal Distribution Fit, by mechanical signal

The lognormal distribution fits all five signals, with the lowest correlation coefficient being 0.979 and the highest being 0.995. The closer the correlation coefficient is to one the better the distribution fits the data.

The expected productivity loss average for each mechanical signal can be seen in table 17 for both years. The greatest productivity loss per signal comes from the flywheel shear bolt and stuffer shear bolt, while lower knotter failure 2 and upper knotter failure have the lowest productivity loss per signal. Between both years, the expected productivity loss is very similar with the greatest difference, of 4 minutes, due to a stuffer shear bolt. The pickup continuous slip has the greatest standard deviation, this is due to the severity of the pickup plugging, at times the operator just has to slow to a stop and other times the plug could take several minutes to unplug.

Table 18: Expected Productivity loss and standard deviation for each mechanical signal by year

Baler Mechanical Signal	Year	Location (μ)	Scale (σ)	N	Expected Productivity Loss (minutes)	2 Year Average Productivity Loss (minutes)	Standard Deviation (minutes)
Flywheel Shear Bolt	2012	2.463	0.7992	72	16	16.5	5
	2013	2.550	0.7405	274	17		5
Lower Knotter Failure 2	2012	1.760	0.7875	96	8	7.5	4
	2013	1.646	0.8110	495	7		4
Pickup Continuous Slip	2012	1.593	1.1090	54	9	9.5	7
	2013	1.615	1.1510	325	10		7
Stuffer Shear Bolt	2012	2.768	0.5462	36	18	16.0	4
	2013	2.415	0.7161	61	14		4
Upper Knotter Failure	2012	1.906	0.5852	594	8	8.0	3
	2013	1.876	0.6622	1535	8		3

Table 18 shows how this impacts overall productivity; the "Upper Knotter Failure" resulted in an average productivity loss of 8 minutes per event. With just over 1000 events occurring, the estimated total productivity loss is approximately 135 hours for 2012 and 394 hours of loss productivity for 2013. This accounts for 52% of the 257 hours of loss productivity due to baler mechanical malfunctions in 2012 and 50% of the 795 hours in 2013. This allows for machinery design improvements to be made to reduce key malfunction downtime. Supply chain managers also have detailed information to more accurately model the supply chain logistics as well as provide resources where they are needed in field.

Table 19: Total Productivity Loss by Mechanical Signal for 2012 and 2013, based on average productivity loss of two years

Baler Mechanical Signal	Event Productivity Loss (h)		Event Productivity Loss (%)	
	2012	2013	2012	2013
Flywheel Shear Bolt	47	163	18	21
Lower Knotter Failure 2	23	92	9	12
Pickup Continuous Slip	25	108	10	14
Stuffer Shear Bolt	26	39	10	5
Upper Knotter Failure	135	394	52	50
Total	257	795	100	100

Idle Time

Event idle time for each mechanical signal also follows a lognormal distribution. Using the same methods previously used for productivity loss, an expected idle time for each signal can be found. Table 19 shows the idle time associated with each mechanical signal. While stopping to repair the malfunction decreases productivity, it could also result in further added costs, if the time it takes to maintenance is long and the tractor is at idle, fuel is being burned. The majority of the time, a simple issue occurred the tractor was left idling. However the machine should always be shut down and the flywheel brake set prior to working on the implement for safety reasons.

Table 20: Expected Idle time and standard deviation for each mechanical signal by year

Baler Mechanical Signal	**Year**	**Location** (μ)	**Scale** (σ)	**N**	**Expected Idle Time** (minutes)	**2 Year Average Idle Time** (minutes)	**Standard Deviation** (minutes)
Flywheel Shear Bolt	2012	2.243	0.8134	72	13	12	5
	2013	1.868	1.0250	271	11		6
Lower Knotter Failure 2	2012	1.688	0.8388	96	8	7	4
	2013	1.216	1.0130	490	6		4
Pickup Continuous Slip	2012	1.348	1.0130	54	6	7	5
	2013	1.183	1.3590	324	8		9
Stuffer Shear Bolt	2012	2.488	0.7754	36	16	12.5	5
	2013	1.599	1.1210	61	9		7
Upper Knotter Failure	2012	1.784	0.6349	594	7	6.5	3
	2013	1.438	0.9181	1525	6		4

Table 20 below shows the total idle time associated with each event, a total of 204 hours and 634 hours were spent in idle while maintaining equipment in 2012 and 2013, respectively. The upper knotter failure is half of the idle time. In 2013, 634 hours of idle time were collected just due to baler mechanical malfunctions; at an average tractor-baler idle fuel rate of 7.7 L h^{-1}. Approximately 5,000 liters of fuel are consumed over the 2013 year while maintaining balers during production.

Table 21: Total Idle Time by Mechanical Signal for 2012 and 2013, based on average Idle Time of two years

Baler Mechanical Signal	Event Idle Time (h)		Event Idle Time (%)	
	2012	2013	2012	2013
Flywheel Shear Bolt	34	119	17	19
Lower Knotter Failure 2	22	86	11	13
Pickup Continuous Slip	19	79	9	13
Stuffer Shear Bolt	21	30	10	5
Upper Knotter Failure	109	320	53	50
Total	204	634	100	100

On average, 46% of the 2.8 hours per day of baler idle time in 2012 can be contributed to these five mechanical signals. The other 54% of the idle time can be contributed to organizational issues, such as waiting for the windrower shredder to make windrows, performing routine maintenance, or when a severe or atypical issue occurs. With a significant amount of idle time each day, the latter of the three is not likely to be the case. While performing routine maintenance, the tractor should be shut off; however, this isn't always the case, which makes the other 54% of idle time undistinguishable between performing routine maintenance and organizational issues. In both cases, the crews can easily correct the idle time by not running the tractor while performing maintenance or change the organizational layout of how the equipment operates.

The additional idle time significantly impacts the supply chain, a 360 horsepower tractor costs about $97 per hour to rent (Edwards et. al, 2014). In 2012, $18,500 was spent just to rent the machine during these five mechanical malfunction repairs; in 2013 this was $61,500. Once in full production, assuming the idle time per malfunction and the same rate of malfunctions occurs, approximately $225,000 will be spent just to pay for hours during the idle time of the five baler downtime instances. Additional costs are also incurred during the idle time such as fuel and labor.

Conclusion

This automated approach of determining downtime associated with balers allows for managers to monitor the main downtime issues. It also allows for a better understanding of why the downtime is occurring, and enables correction. A slight reduction in downtime improves overall productivity. In 2012, if the 46% of idle time that contributed to the five mechanical malfunctions could have been prevented, the average productivity would be above 67% for balers; if just half the time could have been prevented, the average productivity would be approximately 58% compared to the 48% that the crews actually achieved.

Eliminating or reducing productivity loss has significant impact on the supply chain of corn stover. In 2012, during the 257 hours of productivity loss, approximately 7,500 dry tons could have been produced, accounting for 25% of the supply chain for that year. While in 2013, 18,000 dry tons could have been produced during the 795 hours, accounting for 15% of that year's supply chain. Assuming the same rate of malfunctions per bale and the productivity loss remains the same for each individual malfunction, in full production 22% of the supply chain or 170,000 bales could have been produced during the downtime of the five mechanical signals.

Facilitating crews to "dial in" the balers would result in overall productivity increase; while not the entire downtime can be corrected, encouragement to reduce the majority of downtime is essential in order to economically harvest biomass on a commercial scale. The downtime can be corrected by proper training and by field exposure to the equipment; once the operators understand how the equipment works in different conditions, they can make adjustments to improve downtime.

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CHAPTER 4. GENERAL CONCLUSIONS

It is evident that energy security and environmental security are not only concerns at a local and national level, but are also global concerns. The EPA is creating and mandating standard requirements through programs such as the RFS in order to reduce dependence on fossil fuels, reduce greenhouse gas emissions, and increase energy security. Cellulosic ethanol is a viable pathway to help meet the mandates and achieve energy independence. Cellulosic feedstock is abundant throughout the United States in many forms, and is collected differently; however, throughout the entire process of obtaining any forms of the feedstock there is a need to increase productivity and efficiencies.

The common feedstock in the Midwestern United States is corn stover. In order to economically harvest corn stover, the supply chain needs to be carefully monitored and adjusted in order to maximize productivity and reduce costs. In Chapter 2, "Automated Logistics Processing of GIS Data for Agricultural Harvest Equipment", methods were developed and utilized in order to understand machinery and crew productivity on a commercial scale in real time, eliminating an intense hand filtering. Utilizing spatial logging instruments capable of capturing CAN Bus data allowed for instance performance metrics to be extracted and evaluated.

Chapter 2 defines key performance metrics needed in order to understand what occurs with each machine on a daily basis, enabling managers to analyze the performance without having to personally monitor the equipment. The ability to unlock instant performance metrics effectively changes the supply chain in order to increase productivity, which drives down production costs. The integration of telematics provided faster feedback for crews to learn how to improve throughout the season. In 2013, baler productivity increased approximately 8% while idle time decreased by approximately 8.5%.

While productivity is commonly associated with what is happening with equipment, it is also desirable to know what is happening with equipment when they aren't being productive. Chapter 3, "Automated Downtime Analysis of GIS Data for Agricultural Harvest Equipment", focused on the downtime associated with large square balers and the impact this has on productivity. In 2012 and 2013, the idle time associated with large square balers was 42% and 33%, respectively. Understanding how the idle time occurs allows crews to change organizational habits and better "dial in" a machine to reduce downtime.

Chapter 3 defines the major areas of large square balers that commonly have malfunctions while in production, and how it impacts overall productivity. This can be used to direct technicians to the balers to help crews better understand what is happening and to correct the issue. By reducing half of the productivity loss associated with the five main mechanical malfunctions, productivity can be significantly improved, getting them closer to commercial standards.

The methods defined in this paper enables increases in productivity through accurate crew and machine performance evaluations. The data and methods also allow an accurate approach to model the supply chain of corn stover, this is crucial for determining costs and resources needed. This will aid in commercial scale harvesting of corn stover of over 76,800 hectares (190,000 acres) per facility. With over 200 tractors per facility, it is crucial to understand the productivity and downtime of the entire supply chain in a timely and accurate fashion.

APPENDIX

Appendix A: Shredder ANOVA

One-way ANOVA: Crew Active Duration (h) versus Crew

Source	DF	SS	MS	F	P
Crew	3	37.4	12.5	1.23	0.301
Error	211	2144.5	10.2		
Total	214	2182.0			

S = 3.188   R-Sq = 1.72%   R-Sq(adj) = 0.32%

```
                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level    N   Mean  StDev  ------+---------+---------+---------+---
1       20  9.610  3.157           (-----------*-----------)
2       72  8.212  3.931       (-----*------)
3       16  8.032  2.749  (------------*------------)
4      107  8.704  2.651           (-----*----)
                          ------+---------+---------+---------+---
                              7.2       8.4       9.6      10.8
Pooled StDev = 3.188
```

One-way ANOVA: Machine On (%) versus Crew

Source	DF	SS	MS	F	P
Crew	3	1692	564	1.35	0.260
Error	211	88432	419		
Total	214	90125			

S = 20.47   R-Sq = 1.88%   R-Sq(adj) = 0.48%

```
                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level    N   Mean  StDev  --+---------+---------+---------+-------
1       20  79.34  16.75           (------------*------------)
2       72  76.42  24.38             (------*------)
3       16  71.52  20.59  (-------------*-------------)
4      107  71.63  18.05         (----*-----)
                          --+---------+---------+---------+-------
                          63.0      70.0      77.0      84.0
Pooled StDev = 20.47
```

One-way ANOVA: Machine Off (%) versus Crew

Source	DF	SS	MS	F	P
Crew	3	1692	564	1.34	0.261
Error	211	88469	419		
Total	214	90161			

S = 20.48   R-Sq = 1.88%   R-Sq(adj) = 0.48%

```
                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level    N   Mean  StDev  ---+---------+---------+---------+------
1       20  20.66  16.76  (------------*-----------)
2       72  23.58  24.39        (------*-----)
3       16  28.46  20.56        (--------------*-------------)
4      107  28.37  18.06              (-----*----)
                          ---+---------+---------+---------+------
                          14.0      21.0      28.0      35.0
Pooled StDev = 20.48
```

One-way ANOVA: Machine On (h) versus Crew

Source	DF	SS	MS	F	P
Crew	3	37.74	12.58	1.77	0.154
Error	211	1501.96	7.12		
Total	214	1539.70			

S = 2.668   R-Sq = 2.45%   R-Sq(adj) = 1.06%

```
                     Individual 95% CIs For Mean Based on
                     Pooled StDev
Level   N   Mean  StDev  --+---------+---------+---------+-------
1      20  7.525  2.783              (---------*---------)
2      72  6.029  2.944        (----*----)
3      16  5.919  2.661  (----------*----------)
4     107  6.240  2.444           (---*---)
                     --+---------+---------+---------+-------
                     4.8       6.0       7.2       8.4
Pooled StDev = 2.668
```

One-way ANOVA: Production (%) versus Crew

```
Source   DF    SS   MS     F      P
Crew      3   133   44  0.29  0.835
Error   211  32680  155
Total   214  32813

S = 12.45   R-Sq = 0.41%   R-Sq(adj) = 0.00%

                     Individual 95% CIs For Mean Based on
                     Pooled StDev
Level   N   Mean  StDev  --------+---------+---------+---------+-
1      20  70.97  10.44      (---------------*--------------)
2      72  70.54  14.95           (--------*-------)
3      16  69.88  11.74  (-----------------*----------------)
4     107  72.03  10.94                (------*------)
                     --------+---------+---------+---------+-
                         66.5      70.0      73.5      77.0
Pooled StDev = 12.45
```

One-way ANOVA: Idle (%) versus Crew

```
Source   DF       SS     MS     F      P
Crew      3   1656.6  552.2  8.01  0.000
Error   211  14549.9   69.0
Total   214  16206.5

S = 8.304   R-Sq = 10.22%   R-Sq(adj) = 8.95%

                      Individual 95% CIs For Mean Based on Pooled StDev
Level   N    Mean   StDev    +---------+---------+---------+---------
1      20  22.841   7.280               (---------*----------)
2      72  20.162   9.342             (-----*----)
3      16  21.711  10.321            (-----------*-----------)
4     107  15.550   7.364    (---*----)
                          +---------+---------+---------+---------
                      14.0      17.5      21.0      24.5
Pooled StDev = 8.304
Grouping Information Using Tukey Method
Crew   N    Mean  Grouping
1     20  22.841  A
3     16  21.711  A
2     72  20.162  A
4    107  15.550   B
Means that do not share a letter are significantly different.
```

One-way ANOVA: Field Transportation (%) versus Crew

```
Source   DF       SS      MS      F      P
Crew      3   641.04  213.68  31.84  0.000
Error   211  1416.17    6.71
Total   214  2057.21

S = 2.591   R-Sq = 31.16%   R-Sq(adj) = 30.18%

                     Individual 95% CIs For Mean Based on
                     Pooled StDev
Level   N   Mean  StDev  -+---------+---------+---------+--------
1      20  1.042  0.645  (-------*-------)
2      72  1.873  1.354        (---*----)
3      16  2.313  1.373       (-------*--------)
4     107  5.195  3.434                          (---*--)
                     -+---------+---------+---------+--------
```

```
                 0.0      1.5      3.0      4.5
Pooled StDev = 2.591
```

Grouping Information Using Tukey Method

Crew	N	Mean	Grouping
4	107	5.195	A
3	16	2.313	B
2	72	1.873	B
1	20	1.042	B

Means that do not share a letter are significantly different.

One-way ANOVA: Road Transportation (%) versus Crew

Source	DF	SS	MS	F	P
Crew	3	89.2	29.7	0.52	0.669
Error	211	12073.9	57.2		
Total	214	12163.2			

S = 7.565   R-Sq = 0.73%   R-Sq(adj) = 0.00%

```
                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level    N   Mean  StDev  --+---------+---------+---------+-------
1       20  5.362  8.097  (------------*-------------)
2       72  7.628  9.868             (-------*------)
3       16  6.489  6.335    (--------------*--------------)
4      107  7.281  5.590              (-----*-----)
                          --+---------+---------+---------+-------
                          2.5       5.0       7.5      10.0
Pooled StDev = 7.565
```

One-way ANOVA: Effective Area Capacity versus Crew

Source	DF	SS	MS	F	P
Crew	3	16.57	5.52	3.16	0.026
Error	211	368.98	1.75		
Total	214	385.55			

S = 1.322   R-Sq = 4.30%   R-Sq(adj) = 2.94%

```
                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level    N   Mean  StDev  -+---------+---------+---------+--------
1       20  6.781  0.954  (-------*-------)
2       72  7.403  1.435            (----*---)
3       16  8.075  1.007                (--------*---------)
4      107  7.562  1.340              (---*---)
                          -+---------+---------+---------+--------
                          6.30      7.00      7.70      8.40
Pooled StDev = 1.322
```

Grouping Information Using Tukey Method

Crew	N	Mean	Grouping
3	16	8.075	A
4	107	7.562	A B
2	72	7.403	A B
1	20	6.781	B

Means that do not share a letter are significantly different.

Appendix B: Baler ANOVA

One-way ANOVA: Crew Active Duration (h) versus Crew

Source	DF	SS	MS	F	P
Crew	3	19.5	6.5	0.63	0.595
Error	202	2076.4	10.3		
Total	205	2095.9			

S = 3.206   R-Sq = 0.93%   R-Sq(adj) = 0.00%

```
                          Individual 95% CIs For Mean Based on
                          Pooled StDev
```

```
Level  N   Mean  StDev  --+---------+---------+---------+-------
1     50  9.947  2.579         (------------*------------)
2     48  9.200  2.928  (------------*------------)
3     52  9.770  4.414        (------------*-----------)
4     56  9.984  2.537          (-----------*-----------)
                        --+---------+---------+---------+-------
                        8.40      9.10      9.80     10.50
Pooled StDev = 3.206
```

One-way ANOVA: Machine On (%) versus Crew

```
Source   DF     SS   MS     F      P
Crew      3   2628  876  2.11  0.100
Error   202  83849  415
Total   205  86476

S = 20.37   R-Sq = 3.04%   R-Sq(adj) = 1.60%

                        Individual 95% CIs For Mean Based on Pooled StDev
Level  N   Mean  StDev    +---------+---------+---------+---------
1     50  68.92  18.58       (---------*--------)
2     48  67.06  22.13     (---------*--------)
3     52  74.83  24.04              (---------*--------)
4     56  65.51  16.19    (--------*--------)
                          +---------+---------+---------+---------
                        60.0      66.0      72.0      78.0
Pooled StDev = 20.37
```

One-way ANOVA: Machine Off (%) versus Crew

```
Source   DF     SS   MS     F      P
Crew      3   2625  875  2.11  0.100
Error   202  83794  415
Total   205  86419

S = 20.37   R-Sq = 3.04%   R-Sq(adj) = 1.60%

                        Individual 95% CIs For Mean Based on
                        Pooled StDev
Level  N   Mean  StDev  -------+---------+---------+---------+--
1     50  31.10  18.57        (---------*--------)
2     48  32.95  22.11          (---------*---------)
3     52  25.17  24.04  (--------*--------)
4     56  34.48  16.21             (-------*--------)
                        -------+---------+---------+---------+--
                             24.0      30.0      36.0      42.0
Pooled StDev = 20.37
```

One-way ANOVA: Machine On (h) versus Crew

```
Source     DF       SS    MS     F      P
Crew ID     3    19.42  6.47  1.01  0.388
Error     202  1290.03  6.39
Total     205  1309.45

S = 2.527   R-Sq = 1.48%   R-Sq(adj) = 0.02%

                        Individual 95% CIs For Mean Based on
                        Pooled StDev
Level  N   Mean  StDev  --+---------+---------+---------+-------
1     50  6.715  2.261          (-----------*-----------)
2     48  5.982  2.469  (-----------*-----------)
3     52  6.785  3.084            (----------*-----------)
4     56  6.502  2.207        (----------*----------)
                        --+---------+---------+---------+-------
                        5.40      6.00      6.60      7.20
Pooled StDev = 2.527
```

One-way ANOVA: Production (%) versus Crew

```
Source   DF     SS    MS      F      P
Crew      3   9673  3224  23.85  0.000
Error   202  27310   135
Total   205  36984
```

```
S = 11.63   R-Sq = 26.16%   R-Sq(adj) = 25.06%

                    Individual 95% CIs For Mean Based on
                    Pooled StDev
Level   N   Mean  StDev  -------+---------+---------+---------+--
1      50  42.18  10.37    (----*-----)
2      48  40.96  12.46  (----*-----)
3      52  50.87  12.33              (-----*----)
4      56  57.63  11.27                       (----*----)
                         -------+---------+---------+---------+--
                             42.0      48.0      54.0      60.0
Pooled StDev = 11.63

Grouping Information Using Tukey Method
Crew  N   Mean  Grouping
4    56  57.63  A
3    52  50.87    B
1    50  42.18      C
2    48  40.96      C
Means that do not share a letter are significantly different.
```

One-way ANOVA: Idle (%) versus Crew

```
Source    DF     SS    MS      F      P
Crew       3  12700  4233  38.47  0.000
Error    202  22228   110
Total    205  34928

S = 10.49   R-Sq = 36.36%   R-Sq(adj) = 35.42%

                    Individual 95% CIs For Mean Based on Pooled StDev
Level   N   Mean  StDev   -+---------+---------+---------+--------
1      50  49.29   9.54                          (---*----)
2      48  48.36  12.45                          (---*---)
3      52  38.54  11.43              (---*---)
4      56  30.34   8.34   (---*---)
                          -+---------+---------+---------+--------
                         28.0      35.0      42.0      49.0
Pooled StDev = 10.49
Grouping Information Using Tukey Method
Crew   N   Mean  Grouping
1    50  49.29  A
2    48  48.36  A
3    52  38.54    B
4    56  30.34      C
Means that do not share a letter are significantly different.
```

One-way ANOVA: Field Transportation (%) versus Crew

```
Source    DF       SS     MS     F      P
Crew       3    93.39  31.13  4.49  0.004
Error    202  1399.68   6.93
Total    205  1493.07

S = 2.632   R-Sq = 6.25%   R-Sq(adj) = 4.86%

                    Individual 95% CIs For Mean Based on
                    Pooled StDev
Level   N   Mean  StDev  --------+---------+---------+---------+-
1      50  4.195  2.950                (--------*---------)
2      48  3.927  3.344              (--------*--------)
3      52  3.533  2.668          (--------*--------)
4      56  2.461  1.240  (--------*-------)
                         --------+---------+---------+---------+-
                              2.40      3.20      4.00      4.80
Pooled StDev = 2.632
Grouping Information Using Tukey Method
Crew   N   Mean  Grouping
1    50  4.195  A
2    48  3.927  A
3    52  3.533  A B
4    56  2.461    B
Means that do not share a letter are significantly different.
```

One-way ANOVA: Road Transportation (%) versus Crew

```
Source   DF       SS     MS     F      P
Crew      3    733.5  244.5  3.73  0.012
Error   202  13228.1   65.5
Total   205  13961.6

S = 8.092   R-Sq = 5.25%   R-Sq(adj) = 3.85%

                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level   N   Mean   StDev  --+---------+---------+---------+-------
1      50  4.337   4.663  (--------*--------)
2      48  6.811   8.656          (--------*--------)
3      52  7.065   7.750           (--------*--------)
4      56  9.595  10.070                     (-------*--------)
                          --+---------+---------+---------+-------
                          2.5       5.0       7.5      10.0
Pooled StDev = 8.092
Grouping Information Using Tukey Method
Crew   N   Mean  Grouping
4     56  9.595  A
3     52  7.065  A B
2     48  6.811  A B
1     50  4.337    B
Means that do not share a letter are significantly different.
```

One-way ANOVA: Effective Area Capacity versus Crew

```
Source   DF       SS      MS      F      P
Crew      3   584.75  194.92  31.16  0.000
Error   202  1263.58    6.26
Total   205  1848.33

S = 2.501   R-Sq = 31.64%   R-Sq(adj) = 30.62%

                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level   N    Mean  StDev  ------+---------+---------+---------+---
1      50  11.744  2.368  (---*----)
2      48  12.841  2.677        (----*---)
3      52  12.191  1.401    (---*----)
4      56  15.939  3.167                            (---*----)
                          ------+---------+---------+---------+---
                             12.0      13.5      15.0      16.5
Pooled StDev = 2.501
Grouping Information Using Tukey Method
Crew   N    Mean  Grouping
4     56  15.939  A
2     48  12.841    B
3     52  12.191    B
1     50  11.744    B
Means that do not share a letter are significantly different.
```

One-way ANOVA: Bale/day versus Crew

```
Source    DF       SS     MS     F      P
Crew       3   138458  46153  4.56  0.004
Error    181  1832214  10123
Total    184  1970672

S = 100.6   R-Sq = 7.03%   R-Sq(adj) = 5.48%

                      Individual 95% CIs For Mean Based on
                      Pooled StDev
Level   N   Mean  StDev  -------+---------+---------+---------+--
1      49  181.2   92.9           (-------*-------)
2      39  146.2   84.6  (--------*--------)
3      52  207.0  112.6                  (-------*-------)
4      45  221.6  106.6                      (-------*--------)
                         -------+---------+---------+---------+--
                              140       175       210       245
Pooled StDev = 100.6
Grouping Information Using Tukey Method
```

```
Crew  N  Mean  Grouping
4    45  221.6  A
3    52  207.0  A
1    49  181.2  A B
2    39  146.2    B
Means that do not share a letter are significantly different.
```

One-way ANOVA: Flakes/bale versus Crew

```
Source    DF      SS     MS     F      P
Crew       3   961.3  320.4  5.60  0.001
Error    190 10877.1   57.2
Total    193 11838.4

S = 7.566   R-Sq = 8.12%   R-Sq(adj) = 6.67%

                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level  N    Mean  StDev  ------+---------+---------+---------+---
1     50  36.387  5.707     (--------*-------)
2     47  35.786  6.940  (--------*--------)
3     52  39.787  8.914              (-------*-------)
4     45  41.154  8.275                   (--------*--------)
                         ------+---------+---------+---------+---
                             35.0      37.5      40.0      42.5
Pooled StDev = 7.566
Grouping Information Using Tukey Method
Crew  N    Mean  Grouping
4    45  41.154  A
3    52  39.787  A B
1    50  36.387    B C
2    47  35.786      C
Means that do not share a letter are significantly different.
```

One-way ANOVA: bales/hr versus Crew

```
Source    DF     SS   MS     F      P
Crew       3    146   49  0.39  0.757
Error    180  22233  124
Total    183  22379

S = 11.11   R-Sq = 0.65%   R-Sq(adj) = 0.00%

                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level  N   Mean  StDev  -----+---------+---------+---------+----
1     49  59.16  11.10         (------------*-----------)
2     38  58.19  11.19     (-------------*-------------)
3     52  56.83   9.82  (-----------*-----------)
4     45  57.54  12.40    (------------*------------)
                        -----+---------+---------+---------+----
                           55.0      57.5      60.0      62.5
Pooled StDev = 11.11
```

One-way ANOVA: Fuel Consumption versus Crew

```
Source    DF      SS      MS     F      P
Crew       3  0.5160  0.1720  7.31  0.000
Error    180  4.2354  0.0235
Total    183  4.7513

S = 0.1534   R-Sq = 10.86%   R-Sq(adj) = 9.37%

                         Individual 95% CIs For Mean Based on Pooled StDev
Level  N    Mean   StDev  ---------+---------+---------+---------+
1     49  0.5919  0.1521  (-------*------)
2     38  0.6111  0.1334     (-------*-------)
3     52  0.6171  0.1043      (------*------)
4     45  0.7277  0.2084                    (------*-------)
                          ---------+---------+---------+---------+
                                 0.600     0.660     0.720     0.780
Pooled StDev = 0.1534
Grouping Information Using Tukey Method
Crew  N    Mean  Grouping
```

```
4     45  0.7277  A
3     52  0.6171     B
2     38  0.6111     B
1     49  0.5919     B
```

Means that do not share a letter are significantly different.

Appendix C: 2012 vs 2013 Shredder ANOVA

One-way ANOVA: Crew Active Duration versus Year

```
Source   DF      SS    MS     F      P
Year      1     1.2   1.2  0.08  0.774
Error   669  9870.3  14.8
Total   670  9871.5

S = 3.841   R-Sq = 0.01%   R-Sq(adj) = 0.00%

                        Individual 95% CIs For Mean Based on
                        Pooled StDev
Level    N   Mean  StDev   -+---------+---------+---------+--------
2012   215  8.573  3.193   (----------------*----------------)
2013   456  8.482  4.111     (-----------*-----------)
                           -+---------+---------+---------+--------
                          8.10      8.40      8.70      9.00
Pooled StDev = 3.841
```

One-way ANOVA: Machine On (%) versus Year

```
Source   DF      SS    MS     F      P
Year      1    1258  1258  2.81  0.094
Error   669  299456   448
Total   670  300714

S = 21.16   R-Sq = 0.42%   R-Sq(adj) = 0.27%

                        Individual 95% CIs For Mean Based on
                        Pooled StDev
Level    N   Mean  StDev  -----+---------+---------+---------+----
2012   215  73.94  20.52            (-------------*-------------)
2013   456  71.01  21.45  (---------*---------)
                          -----+---------+---------+---------+----
                             70.0      72.0      74.0      76.0
Pooled StDev = 21.16
```

One-way ANOVA: Production (%) versus Year

```
Source   DF      SS    MS      F      P
Year      1    2323  2323  10.75  0.001
Error   669  144596   216
Total   670  146919

S = 14.70   R-Sq = 1.58%   R-Sq(adj) = 1.43%

                        Individual 95% CIs For Mean Based on Pooled StDev
Level    N   Mean  StDev    +---------+---------+---------+---------
2012   215  71.28  12.38                 (--------*---------)
2013   456  67.29  15.67    (-----*------)
                            +---------+---------+---------+---------
                          66.0      68.0      70.0      72.0
Pooled StDev = 14.70
```

One-way ANOVA: Idle (%) versus Year

```
Source   DF     SS   MS     F      P
Year      1      0    0  0.00  0.973
Error   669  81495  122
Total   670  81495

S = 11.04   R-Sq = 0.00%   R-Sq(adj) = 0.00%

                        Individual 95% CIs For Mean Based on Pooled StDev
Level    N   Mean  StDev   -+---------+---------+---------+--------
2012   215  18.23   8.70   (-----------------*-----------------)
2013   456  18.20  11.98         (-----------*------------)
                           -+---------+---------+---------+--------
```

```
                 16.80     17.60     18.40     19.20
Pooled StDev = 11.04
```

One-way ANOVA: Production out of crew Active versus Year

Source	DF	SS	MS	F	P
Year	1	3782	3782	10.19	0.001
Error	669	248227	371		
Total	670	252010			

S = 19.26   R-Sq = 1.50%   R-Sq(adj) = 1.35%

```
                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level    N   Mean  StDev  ----+---------+---------+---------+-----
2012   215  53.46  18.89                (---------*---------)
2013   456  48.37  19.43  (------*-------)
                          ----+---------+---------+---------+-----
                            47.5      50.0      52.5      55.0
Pooled StDev = 19.26
```

One-way ANOVA: Transportation (%) versus Year

Source	DF	SS	MS	F	P
Year	1	4456	4456	13.82	0.000
Error	669	215718	322		
Total	670	220174			

S = 17.96   R-Sq = 2.02%   R-Sq(adj) = 1.88%

```
                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level    N   Mean  StDev  -------+---------+---------+---------+--
2012   215  10.64   8.33  (---------*--------)
2013   456  16.16  21.01                     (------*-----)
                          -------+---------+---------+---------+--
                              10.0      12.5      15.0      17.5
Pooled StDev = 17.96
```

Appendix D: 2012 vs 2013 Baler ANOVA

One-way ANOVA: Crew Active Duration versus Year

Source	DF	SS	MS	F	P
Year	1	7.9	7.9	0.49	0.485
Error	784	12636.7	16.1		
Total	785	12644.5			

S = 4.015   R-Sq = 0.06%   R-Sq(adj) = 0.00%

```
                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level    N   Mean  StDev  ----+---------+---------+---------+-----
2012   206  9.738  3.198  (-----------------*-----------------)
2013   580  9.511  4.267  (----------*----------)
                          ----+---------+---------+---------+-----
                             9.30      9.60      9.90     10.20
Pooled StDev = 4.015
```

One-way ANOVA: Machine On (%) versus Year

Source	DF	SS	MS	F	P
Year	1	471	471	0.99	0.319
Error	784	371741	474		
Total	785	372212			

S = 21.78   R-Sq = 0.13%   R-Sq(adj) = 0.00%

```
                       Individual 95% CIs For Mean Based on Pooled StDev
Level    N   Mean  StDev    +---------+---------+---------+---------
2012   206  69.05  20.54    (--------------*--------------)
2013   580  70.81  22.20              (--------*--------)
                            +---------+---------+---------+---------
                          66.0      68.0      70.0      72.0
```

Pooled StDev = 21.78

One-way ANOVA: Production (%) versus Year

```
Source  DF      SS    MS      F      P
Year     1    8944  8944  43.95  0.000
Error  784  159561   204
Total  785  168505

S = 14.27   R-Sq = 5.31%   R-Sq(adj) = 5.19%

                        Individual 95% CIs For Mean Based on
                        Pooled StDev
Level    N   Mean  StDev  ------+---------+---------+---------+---
2012   206  48.29  13.43  (------*-----)
2013   580  55.96  14.55                        (---*--)
                          ------+---------+---------+---------+---
                             48.0      51.0      54.0      57.0
Pooled StDev = 14.27
```

One-way ANOVA: Idle (%) versus Year

```
Source  DF      SS     MS      F      P
Year     1   10487  10487  63.74  0.000
Error  784  128992    165
Total  785  139478

S = 12.83   R-Sq = 7.52%   R-Sq(adj) = 7.40%

                        Individual 95% CIs For Mean Based on
                        Pooled StDev
Level    N   Mean  StDev  ----+---------+---------+---------+-----
2012   206  41.21  13.05                        (----*-----)
2013   580  32.90  12.75  (---*--)
                          ----+---------+---------+---------+-----
                           33.0      36.0      39.0      42.0
Pooled StDev = 12.83
```

One-way ANOVA: Transportation (%) versus Year

```
Source  DF       SS     MS     F      P
Year     1    238.1  238.1  2.40  0.122
Error  784  77715.5   99.1
Total  785  77953.6

S = 9.956   R-Sq = 0.31%   R-Sq(adj) = 0.18%

                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level    N    Mean   StDev  --------+---------+---------+---------+-
2012   206  10.525   8.848  (------------*-------------)
2013   580  11.777  10.320                 (-------*-------)
                            --------+---------+---------+---------+-
                                 10.0      11.0      12.0      13.0
Pooled StDev = 9.956
```

One-way ANOVA: Production out of crew Active versus Year

```
Source  DF      SS    MS      F      P
Year     1    6115  6115  22.45  0.000
Error  784  213592   272
Total  785  219707

S = 16.51   R-Sq = 2.78%   R-Sq(adj) = 2.66%

                        Individual 95% CIs For Mean Based on
                        Pooled StDev
Level    N   Mean  StDev  ----+---------+---------+---------+-----
2012   206  33.69  13.78  (--------*--------)
2013   580  40.04  17.37                        (----*-----)
                          ----+---------+---------+---------+-----
                           32.5      35.0      37.5      40.0
Pooled StDev = 16.51
```

ACKNOWLEDGEMENTS

I would first like to thank DuPont for funding this research and providing the opportunity to be engaged with leading edge agriculture. I would also like to thank my major professor, Dr. Matt Darr, for the experience and opportunities this research has provided me. The overwhelming amount of knowledge I have gained throughout the course of this research has developed me professionally and personally.

I would also like to thank my committee member, Dr. Brian Steward, for his guidance and support throughout this research as well as my academic career. I would also like to thank my committee member, Dr. Carl Bern, for taking me on as an undergraduate researcher and engaging me in research early in my college career. The work and experience that we shared together lead me to pursue a degree beyond the Bachelor's. The knowledge, wisdom and stories I have gained while working under Dr. Carl Bern is outstanding and will forever be appreciated.

In addition I would like to thank the research team I have been a part of, especially Levi Powell, Benjamin Covington, Brittany Schon, Keith Webster, Ryan Bergman, and Jeremy Brue. Throughout this research, we have engaged in many projects and accomplished many goals that seemed out of reach; however, with our teamwork, we conquered them all.

Finally, I would like to thank my entire family for being supportive and understanding, throughout my life and academic journey. The encouragement and love I have received has made me the person I am today, and I am forever thankful for your support, guidance and motivation.